Airline Alliance Revenue Management: Improving Joint Revenues through Partner Sharing of Flight Leg Opportunity Costs

ARCHIVES

by

Alyona Michel

A.A., Bard College at Simon's Rock (2003)
B.S., Northeastern University (2008)

Submitted to the Department of Civil and Environmental Engineering in partial fulfillment of the requirements for the degree of

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Author ....
Department of Civil and Environmental Engineering
August 15, 2012

Certified by ....
Peter P. Belobaba
Principal Research Scientist of Aeronautics and Astronautics
Thesis Supervisor

Accepted by ....
Heidi M. Nepf
Chair, Departmental Committee for Graduate Students

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Abstract

Airlines participating in alliances offer code share itineraries (with flight segments operated by different partners) to expand the range of origin-destination combinations offered to passengers, thus increasing market share at little cost. The presence of code share flights presents a problem for airline revenue management (RM) systems, which aim to maximize revenues in an airline's network by determining which booking requests are accepted. Because partners do not jointly optimize revenues on code share flights, alliance revenue gains from implementing advanced RM methods may be lower than an individual airline's gains. This thesis examines seat availability control methods that alliance partners can adopt to improve the total revenues of the alliance without formally merging. Partners share information about the opportunity costs to their network, called "bid prices", of selling a seat on their own flight leg, a mechanism termed bid price sharing (BPS).

Results show that BPS methods often improve revenues and work best for networks with certain characteristics and partners with similar RM systems that exchange recently calculated bid prices as often as possible. Gains are typically only achieved if both alliance partners participate in the code share availability decision (called dual control) rather than one partner only, but implementation of dual control is more difficult for airlines in practice. In the best case scenario, gains of up to .40% where achieved, which can translate into $120 million per year for the largest airlines. In our simulations, BPS with dual control and frequent bid price calculation and exchange was the only method that produced consistently positive revenue gains in all the scenarios tested. Therefore, alliance airlines must consider the trade off between revenue gains and implementation difficulties of more frequent bid price exchange or dual control.

Thesis Supervisor: Peter P. Belobaba
Title: Principal Research Scientist of Aeronautics and Astronautics

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My interest in transportation has been present for much longer than I knew what to call it. While traveling, I constantly planned the logistics of trips in detail, deciding the best routes to take and thinking how to improve the existing transportation systems of the cities I visited to make them more efficient. The existence of the

MST program allowed me to realize this interest and develop it into a formal education that can be applied to real-world transportation problems. I wholeheartedly thank the MST program's organizers for that opportunity. Watching the Transportation@MIT lectures online before I applied to MIT helped me to better understand the research philosophy of the Institute in the area of Transportation, and it was indeed the best choice for my graduate education. In particular, thanks to Nigel Wilson, Amedeo Odoni, Cindy Barnhart, Moshe Ben Akiva, Fred Salvucci, George Kocur, and all the TAs, who have all taught insightfully and provided inspiration and guidance during my coursework in the MST program.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

In recent years, airline alliances have been growing in importance to airlines and passengers. The first global alliance, Star Alliance, was formed in 1997, followed by oneworld (1999) and SkyTeam (2000). As of the completion of this thesis, these three alliances currently have a joint total of 58 members. In 2010, they accounted for about 60% of worldwide airline traffic in terms of passenger-kilometers flown (Backofen, 2010). Table 1.1 presents some facts about the 3 global alliances.

Alliance	Star Alliance	SkyTeam	oneworld
Members*	27	17	14
Formed	1997	2000	1999
Passengers (millions)	679	531	324
Destinations Served	1,356	983	870
Countries	193	178	152
% Market Share† (Revenue Passenger Kilometers)	26.4	16.6	15.9
Revenue ($billions)	182	149	106
$ per Employee (000s)	417	359	382
$ per Aircraft (000s)	41,056	37,176	42,130
Flights	21,555	14,816	9,239
Lounges	990+	503	584
Employees	436,000	414,686	277,500
Aircraft	4,433	4,008**	2,516

*Including members elect. †For the year 2010. **Including affiliated carriers.
Sources: Company websites, and Backofen (2010)

Table 1.1: Global Alliances Facts and Figures for 2011

Cooperation between airlines for mutual benefit has been occurring much longer than the existence of global alliances. A variety of coordination activities can be undertaken by participating airlines for their mutual benefit, with the goal of both improving revenues and cutting costs. Figure 1-1 presents a list of cooperation activities that airlines may engage in, in order of increasing commitment. This thesis focuses on code sharing, which occurs when a flight leg operated by one carrier is marketed and sold by another carrier under a different flight designator code. Though code sharing is extensively practiced within global alliances, it also occurs domestically in regional alliances and on a route-specific basis among carriers outside of an alliance, and need not imply that further cooperation is undertaken.

Increasing Commitment	**Alliance Activity**
↓	Code sharing (the topic addressed in this thesis)
	Scheduling of flight arrival and departure times
	Location of arrival and departure gates
	Joint frequent flyer programs
	Share of airport lounges and other ground facilities
	Share of passenger services like baggage handling and check-in
	Share of support services like maintenance and catering
	Share of distribution and retailing functions
	Joint purchasing of such items as fuel, passenger service goods and aircraft
	Joint advertising campaigns and creation of a common brand
	Joint allocation of resources (fleet and crew planning)
	Equity investment in partner's stock

Figure 1-1: Activities Engaged in by Alliances in Order of Increasing Commitment. Adapted from de la Torre (1999)

To better understand code sharing, first consider the differences between supply and demand for air travel. Airline supply consists of flight legs operated from one airport to another, whereas consumers demand transportation from their origin city to their destination. A ticketed customer flies on an itinerary that may consist of a single (local) flight leg, or may require connections and consist of multiple flight legs. The three flight legs shown in Figure 1-2 allow a number of origin-destination (O-D) combinations to be sold to customers (3 local, 2 single connection, and 1 double-connection itinerary).

In this example, alliance partner United Airlines (UA) operates the flights from Denver (DEN) to Chicago (ORD) and ORD to Frankfurt (FRA), and Lufthansa (LH) operates the flight from FRA to Budapest (BUD). The asterisk (*) indicates that the flight is marketed as a code share. The alliance partner that sells the itineraries is referred to as the marketing partner. The partner that operates the code share flight leg, which was sold by a code share partner, is called the operating partner. The three components of alliance traffic are:

1. **Own local** passengers traverse a single flight leg such that their origin and destination are those of the flight leg. In this example, a passenger flying DEN to ORD is an own local passenger of operating and marketing airline UA.

2. **Own connecting** passengers traverse multiple flight legs of the same airline to go from their origin to their destination. A passenger flying from DEN to FRA via ORD, with all flights operated and marketed by UA, is an own connecting passenger of UA.

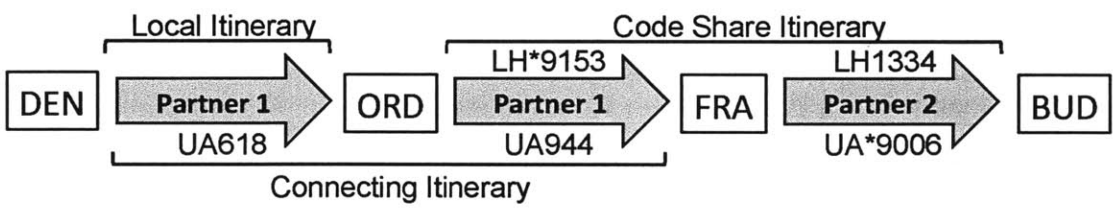

Figure 1-2: Traffic Components in Alliances

3. **Code share** passengers traverse one (or more) flight legs of the airline selling the code share itinerary (the marketing carrier) and one (or more) legs operated by the operating carrier. A code share flight that is operated by another carrier is designated by the marketing airline's code, such as United's UA or Lufthansa's LH, followed by an asterisk to indicate that the flight is operated by a partner. In this example, the flight number associated with the ORD to FRA flight leg is either UA944 or LH*9153, depending on which airline sold the itinerary. A passenger flying from ORD to BUD, having booked through either

UA or LH, using UA's operated flight leg ORD to FRA, and LH's operated flight leg FRA to BUD, is a code share passenger.

1.1 Code Sharing for Competitive Advantage

Passenger airlines engage in code sharing in an effort to improve market share by providing access to new O-D markets and airports at a much smaller incremental operating cost than if an airline were to use its own aircraft and own station personnel. The first code sharing agreement went into effect in 1967, when Allegheny Airlines code shared to cut costs by using a regional carrier that could economically serve small short-haul markets because it had smaller aircraft (Oster and Pickrell, 1988). Code sharing with regional (also called commuter) carriers is extremely common in US domestic markets, where the larger network carrier feeds its long-haul routes with passengers from smaller markets, supplied by regional carriers. Network airlines such as Delta even use brand recognition to improve perceived seamlessness, such as flights marketed as Delta Connection.

The first international code sharing agreement was signed in 1985 between Qantas and American Airlines (Gellman Research Associated, 1994), and provided the Australian carrier with access to the US domestic market, and vice versa. Code share agreements between two large international airlines can provide more symmetric benefits than regional alliances because the international routes are fed by each partner's domestic network. The local member airline is familiar with its own local market, and passengers are familiar with their local airline. An allied airline entering a new market does not need to build its own network and gain market share, but rather relies on its partner to feed traffic, and effectively expands its network coverage as if it served its partner's destinations.

Airlines also code share with carriers outside of their alliances for marketing and ease of interline ticket sales, both domestically and internationally. However, these types of point-to-point agreements are not usually for strategic reasons, as are the international alliances, which are more strongly integrated. An agreement founded on long term goals can be termed strategic (de la Torre, 1999).

Access to an operating partner's seats depends on the type of agreement (Vinod, 2004). Block space arrangements allow the marketing partner to buy a number of seats from the operating carrier at a fixed price, and the seat inventory available to the operating carrier is reduced. The marketing carrier then controls the sale of those seats as if they were its own. Agreements are usually in place to allow the repurchase of unused block space seats by the operating carrier as needed. Free sale agreements allow direct access to the operating partner's inventory as long as there are seats available at the ticket fare level, and are more prevalent than block space agreements, according to Vinod (2004). This thesis assumes a free sale arrangement between the alliance partners.

There are different types of code sharing agreements, depending on the intent of the airlines. For example, the intent may be to create an internationally recognized alliance brand, or to provide service to small regional markets that are fed from a larger domestic market. The various types of code sharing agreements are summarized below (adapted from Jain (2011)).

1. **Parallel code sharing** occurs between two partners on a route which is operated by both of them, such as flights between their hubs.

2. **Complementary code sharing** occurs when partners use each others' flights to provide connecting service to markets which are out of their own network. Complementary code sharing increases the number of destinations served by an airline, thus attracting passengers without incurring incremental operating costs.

3. **Strategic code sharing** occurs on a vast number of routes so as to strategically link both airlines' networks. Seats are accessed between the partners using a free sale agreement (de la Torre, 1999), so as to provide seamless availability.

1.2 Potential Impacts of Code Sharing

There can be benefits and detriments attributed to the practice of code sharing. Passengers can benefit from a larger choice of flight itineraries and fares resulting from the expansive networks of alliances, as well as seamless check in, connecting flight transfers, baggage transfers, and aggregate earnings on an alliance's participating frequent flier programs. An important revenue source for the alliances, business passengers especially benefit from faster status achievement on coordinated frequent flier programs and lounge access.

If a code share agreement results in reduced service frequency, flight options decrease, and the resulting scheduled flights may not satisfy the passenger in terms of desired departure or arrival times. Reduced competition on hub-to-hub flights may also result in more market power for the supplying airline, thus causing price increases. Brueckner (2001) found that prices on most routes decreased as a result of code sharing in alliances. However, the opposite occurred for hub-to-hub routes (routes between the alliance hubs), where the service frequency is higher, thus providing a better level of service to customers, and resulting in greater market share for the combined alliance, as well as higher prices for customers.

If code sharing results in the consolidation of flights between hubs into a single flight with a larger airplane, this can also provide environmental benefits. Costly passenger delays at the participating airports could be reduced, where the delays from congestion caused by intense schedule competition of airlines (Vaze, 2011) are a negative externality that may be corrected by market forces in the case of airline alliances.

1.3 Motivation for this Research

In the absence of alliances, an airline carries its own local and connecting passengers, and the sale of interline itineraries is governed by the rules set forth by the International Air Transport Association (IATA) concerning Multilateral Interline Traffic Agreements. Payments to the operating carrier, for the services of carrying passengers and other services such as baggage handling, are processed through the IATA clearing house. Adding code share agreements presents two new challenges, namely managing the code share flight requests and dividing the revenues among the partners according to alliance agreements, which may then be modified on a bilateral or route-specific basis between individual airlines. This thesis discusses and proposes solution options for the problem of managing code share flight requests for the improvement of joint alliance revenues.

The practice of code sharing evolved from interlining, but requires a deeper commitment among the participants than simple interlining. Although it is possible for a passenger to buy an itinerary that consists of the same flight legs as an interline itinerary himself (by purchasing separate local tickets from the two airlines) flying on an interline ticket is easier, typically less expensive, and uses a single ticket with coordinated baggage handling. Code sharing allows the marketing carrier to also add its own designator code to the itinerary and market it as its own product, which provides the added benefit of appearing earlier than interline ticket options on a travel agent's reservations screen.

Parallels and relevant research findings can be extended to other industries where two or more service providers must coordinate their service activities to provide the customer with a single product that can be sold by either service provider. The most common research examples can be found in freight shipping and airline cargo, where different providers transport goods along different segments of the itinerary. The customer requesting the transport of goods is indifferent to the route along which they are transported and by whom, and it is up to the service providers to determine how they will cooperate to service the customer.

The practice of revenue management (RM) intends to maximize revenues through allocation of seats on individual flight legs to different O-D passengers. Different prices can be charged for the same seats because passengers have different willingness-to-pay (WTP) for their flights due to the market characteristics of the many different O-D city pairs served by each flight (further explained in Chapter 2). Without alliances, each airline's RM system maximizes the individual airline's revenues, considering only local and connecting traffic. The existence of code share traffic is problematic for RM. An important concern must be addressed: how to determine availability for code share itineraries.

Modern revenue management systems estimate "bid prices", which represent the value to the network of empty seats on an airline's flight legs, and may be viewed as an opportunity cost to the airline of filling a seat and removing it from the available inventory. The bid prices are calculated by the revenue management system, and can be quite different, as discussed in Chapters 2 and 3. Using a simulation model called the Passenger Origin-Destination Simulator (PODS), this thesis examines a method called bid price sharing, in which airlines exchange bid prices to inform each other of the opportunity cost of selling a partner's seat as part of a code share itinerary. It is hypothesized that bid price sharing produces improved control of seat availability for the alliance's code share itineraries and increases total alliance revenues. This thesis's goal is to present the range of revenue gains, and the effects on local, connecting, and code share traffic and revenues of alliance partners, resulting from different forms of bid price sharing. The range of changes depends on bid price calculation, the structure of the alliance networks, the timeliness of their exchange and recalculations, and whether both or one partner participate in the availability decision. The causes of the revenue changes and the trade-offs facing the airlines concerning the methods' implementation are discussed.

1.4 Overview of the Thesis

Chapter 1 introduced why alliances are significant to industry and consumers. Airline alliances were defined, including the reasons for their formation, key activities engaged in by alliances, including the impacts of code sharing in particular, and the motivation for this thesis was discussed. Chapter 2 gives the reader background on relevant prior work in revenue management. It then reviews more recent literature on alliances, namely work on managing code share itinerary requests and division of code share revenues. Chapter 3 describes the methodology used in the research experiments, providing an overview of PODS, the structure of the two hypothetical alliance network environments used in our experiments, and the dimensions of bid price sharing tested in the thesis experiments.

Chapter 4 presents the findings of bid price sharing among alliance partners in a hypothetical four-airline US-based network with a single alliance consisting of 2 partner airlines. It gives the range of changes when alliance partners use various combinations of revenue management methods, types of bid prices, and management of code share availability. Chapter 5 presents results in a trans-Atlantic network with 2 competing alliances, and examines the differences in the results from the structurally-different US network. Conclusions related to the findings of the thesis and implications for airlines are presented in the last chapter, as well as recommendations for future research.

Chapter 2

Background and Literature Review

Revenue maximization for airlines occurs in stages: in the long-term with network and fleet planning and in the medium term with scheduling, fleet and crew assignment. In the short term, when the route, schedule and aircraft choices are fixed, the last chance to improve revenues is the revenue management step. In this chapter, a brief overview of revenue management in general is presented, referencing the relevant methods considered in this thesis, followed by revenue management as it relates to airline alliances, focusing on the aspects relevant to the thesis experiments. Good reviews of revenue management can be found in McGill and van Ryzin (1999) and Barnhart et al. (2003).

When airlines began offering discounted fare products with advance purchase requirements in the 1970s, it became necessary to control the number of discounted seats made available for sale. There was revenue to be gained from filling seats in the economy cabin that would not otherwise be booked at full fares, but there was a danger that discount fare passengers could displace later-booking full fare passengers and cause revenue losses. Since US airline deregulation in 1978, fare structures have evolved beyond the two-fare level (or fare class) distinction, with many fare classes on offer.

2.1 Differential Pricing

Airlines typically offer multiple "fare products" to customers because the air transport sector is a high-fixed cost industry, where traditional pricing strategies may not allow the recovery of costs. Airlines cannot price at marginal cost because the marginal cost of flying an additional passenger is near zero if there are seats on the plane. As illustrated in Figure 2-1, charging a single, revenue-maximizing price will not cover costs if the average costs of producing a given quantity are higher than the price consumers are willing to pay for that quantity. In this example, consumers demand 100 units at $200, but the airline must sell 120 to cover costs.

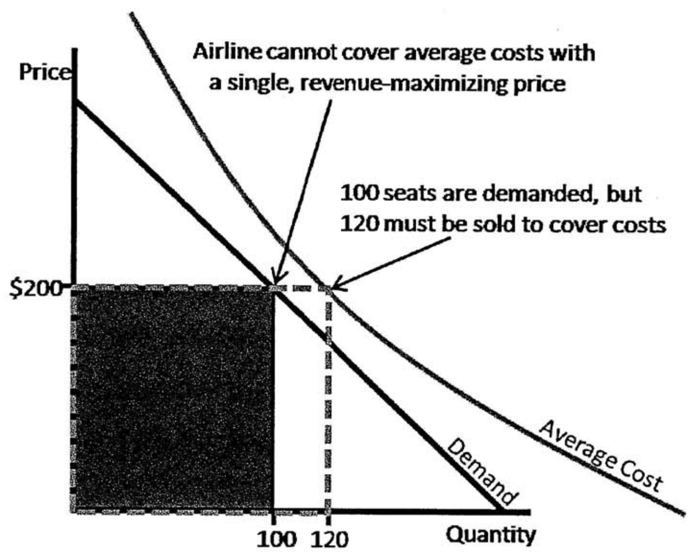

Figure 2-1: A Single Price Does Not Cover the Airline's Costs

Airlines practice price discrimination, or product differentiation, to cover their costs. Often referred to as "differential pricing", the idea is to group passengers according to their willingness-to-pay for travel, particularly into business and leisure segments. For additional discussion on differential pricing, see Dar (2006) or Chapter 3 of Belobaba et al. (2009). The many discounted fares aimed at leisure passengers come with restrictions (or fences) such as requirements on minimum stay, advanced purchase, and non-refundability. These fences attempt to prevent the diversion to discounted fares of business passengers who are willing to buy the restriction-free full fare tickets.

The fare class distinctions, comprised of different price points and restrictions, make up a "fare structure". Fare structures may be more or less restricted, depend-

Fully Restricted

Class	Days AP	Min Stay	Cancel Fee	Change Fee
1	0	No	Yes	No
2	0	No	Yes	Yes
3	10	Yes	Yes	No
4	10	Yes	No	Yes
5	14	Yes	Yes	Yes
6	21	No	Yes	No

Semi Restricted

Class	Days AP	Min Stay	Cancel Fee	Change Fee
1	0	No	No	Yes
2	0	No	No	Yes
3	7	No	Yes	Yes
4	7	No	Yes	Yes
5	14	No	Yes	Yes
6	14	No	No	Yes

Figure 2-2: Example of Fully- and Semi-Restricted Fare Structures, developed for Alliance Network A4 in Jain (2011)

ing on the number and strictness of fences applied to lower fare products. An example of "fully" and "semi" restricted fare structures is provided in Figure 2-2. Successful demand segmentation generates more revenue and higher load factors than charging a single price in two ways: on the high end, from charging business passengers closer to their WTP, and on the low end, by stimulating extra leisure demand from those who would not pay the higher, profit-maximizing price, as illustrated in Figure 2-3.

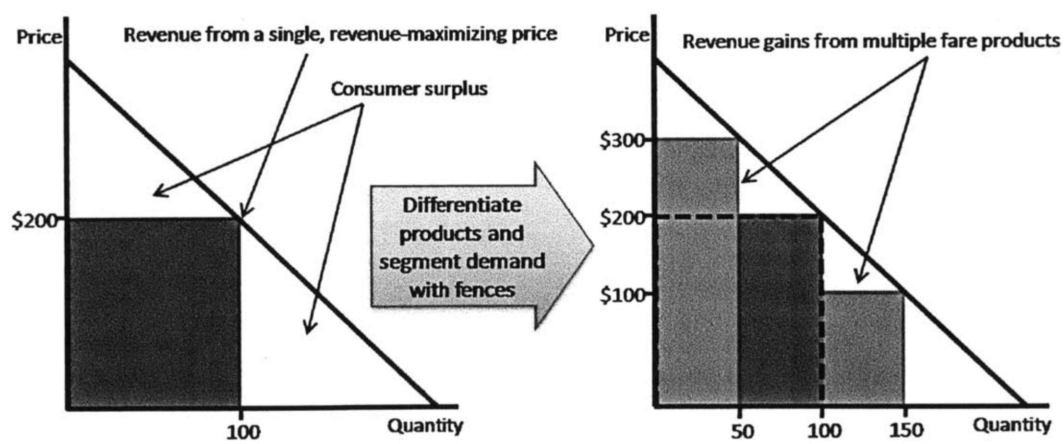

Figure 2-3: Revenue Gains by Segmenting Demand using Fare Products

The determination of seat protections for the full fare passengers from the passengers who arrive earlier seeking discounted fares is called seat inventory control or seat allocation. These seat protections translate to booking limits on the lower classes. An illustration of booking limits is provided in Figure 2-4. No simple rule (such as protecting a percentage of seats) will maximize revenues, because demands change by time, date, and market. Seat allocation methods include leg-based (which maximizes revenues on an individual flight leg) and network-based (which attempts to maximizes revenues over the entire network). Provided in Sections 2.3 and 2.4 are summaries of some of the key seat allocation methods that will be referenced in the methodology and results portions of the thesis.

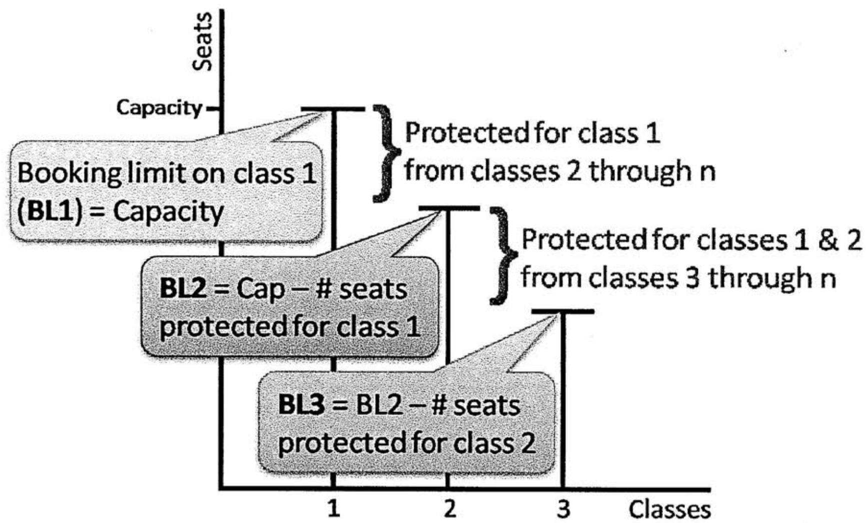

Figure 2-4: Nested Booking Limits on Discounted Fare Classes, Adapted from Cleaz-Savoyen (2005)

2.2 Forecasting

Seat allocation models require detailed forecasts of demand. Forecasts by fare class of mean demand and variance are needed (by flight leg for leg-based optimization and by itinerary for network-based). A method called pickup forecasting (or the additive method) relies on averaging a number of historical observations of incremental bookings, or "pick up" (from the current day t up to departure), to obtain an estimate of the number of bookings to come (i.e, forecast at departure (day 0) = actual bookings (day t) + average pickup (day t to 0)). A discussion of pickup forecasting can be found in Skwarek (1996) on pp. 43-45. More information on forecasting can also be found in the master's thesis of Zickus (1998).

There may be missing or incomplete observations in historical data for fare classes if they were closed at any time by the seat allocator. Correcting for these observations is called unconstraining. A simple method called booking curve unconstraining (also called booking profile and multiplicative unconstraining in the literature) uses historical observations in which the fare class remained open up to departure. It obtains a ratio of bookings at departure to the last day t that the fare class was open, (i.e., forecast at departure (day 0) = actual bookings (day t) * average pickup ratio(Day t to Day 0). For more information and a comparison of the performance of forecasting methods, refer to Weatherford and Kimes (2003), Weatherford and Polt (2002) and Queenan et al. (2007).

2.3 Leg-Based Revenue Management

The early research on the seat allocation problem aimed to find booking limits on seats available at discounted fares, on a single flight leg, so as to maximize expected revenues. It was proposed by Littlewood (1972) that a discount fare booking should be accepted if its revenue exceeds the expected revenue from future full fare bookings (i.e., the product of the full fare value with the probability of arrival of a full fare booking request) and is referred to as Littlewood's Rule for the two class seat inventory control problem.

2.3.1 Expected Marginal Seat Revenue

Littlewood's Rule was extended to multiple fare classes and termed EMSR (expected marginal seat revenue) by Belobaba (1987) in his PhD thesis and subsequent paper (Belobaba, 1989). The EMSR method was later refined to produce better results and termed EMSRb. Though the EMSR heuristic does not produce optimal booking limits for the multi-class case, it provides good approximations, as shown in McGill

(1989) and Wollmer (1992), and is easy to implement compared to optimal but computationally intensive methods (see also Curry (1990), Brumelle and McGill (1993). The idea behind EMSR is to determine how many of the remaining seats on the flight leg to protect for class 1 from earlier-arriving, class 2 or lower passengers. A normal distribution of demand to come by fare class is constructed from forecasts. The number of seats n in fare class k to protect from class $k+1$ depends on the fares for classes k through $k+1$, F_k, and the normal probability distribution (mean and variance) of the demands x_k for each fare class.

$$F_k * Prob(x_k \geq X) \geq F_{k+1} \tag{2.1}$$

The idea is to protect the number of seats n for fare class k so long as the above equation is satisfied. When there are multiple top fare classes (for example, classes 1 and 2) to protect from a lower class $k+1$, weighted average fares, total demands and joint variances are constructed for the multiple top classes before applying 2.1. The method is also useful for providing expected values for each seat on a flight leg. The critical EMSR value (or EMSRc) on a flight leg is the lowest valued available seat at any given remaining available capacity. An illustration is provided in Figure 2-5. If the demand for the flight leg is forecast to be high, then the EMSRc value will be higher than if demand is forecast to be below capacity (in which case the probability of filling the last seat will be small).

2.3.2 Heuristic Bid Price

Heuristic bid price (Belobaba, 2002) is a method that relies on historical data at the flight leg level, but takes steps toward considering network effects. The idea is to accept a connecting passenger if the fare exceeds the sum of the EMSRc values of the flights legs that the connecting itinerary traverses, after modifying this sum downwards. Downward modification is done to account for the potential displacement of local passengers on the flight legs, because selling all the available seats on the flight legs in question to local passengers would produce more revenue than selling

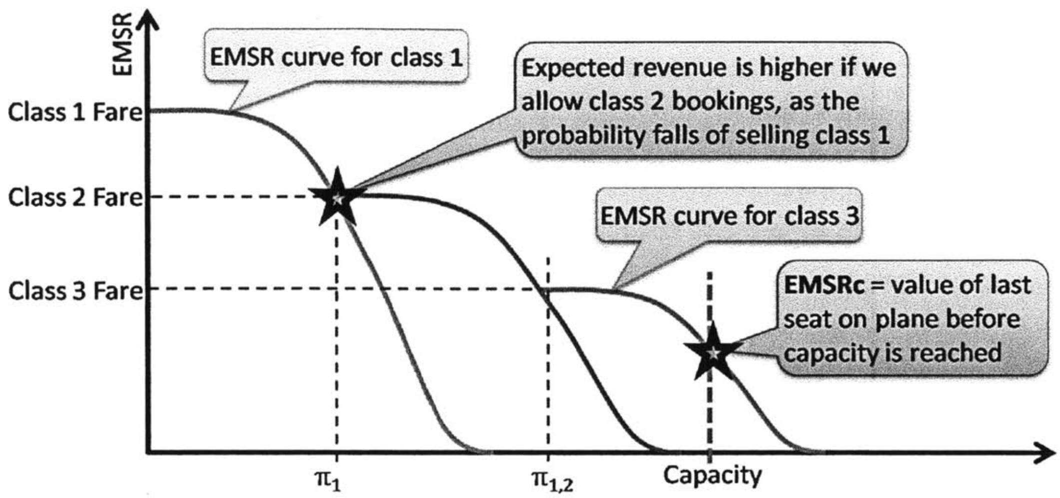

Figure 2-5: Illustration of Expected Marginal Seat Revenue Curves and EMSRc Value, Adapted from Cleaz-Savoyen (2005)

the connecting itinerary (in the same fare class). Let d represent the probability of displacing a local passenger on the 1st flight leg times the probability of displacing a local passenger on the second flight leg. We accept a connecting passenger if the fare for itinerary j F_j exceeds the sum of the EMSRc values on flight legs 1 and 2, $EMSRc_1$ and $EMSRc_2$, with the smaller of the two multiplied by the displacement factor d.

$$F_j \geq Max(EMSRc_1, EMSRc_2) + d * Min(EMSRc_1, EMSRc_2) \qquad (2.2)$$

2.4 Network-Based Revenue Management

Maximizing revenues at the network level requires finding limits on discounted fares available, or simply deciding which booking requests to accept or reject, for each origin-destination itinerary that traverses a flight leg. Mathematical formulations that found optimal partitioned booking limits for each origin-destination fare, or ODF, were not successful because booking limits were on each individual ODF, and were not nested, so seats could go empty that might otherwise be sold to a different ODF request, or requests for a high-revenue ODF could be rejected because the booking limit for that particular ODF had been reached. The benefits of nesting can be achieved by grouping different ODFs into virtual buckets, according to their revenue contribution to the network. Booking limits can then be determined for the lower buckets. Another approach is to determine bid prices, or minimum values for a seat on a flight leg, that an ODF's revenue must exceed. A discussion and analysis of origin-destination control methods, and the use of shadow prices as opportunity costs, is provided in the dissertation of Williamson (1992), and bid price techniques are discussed in Talluri and van Ryzin (1998) . Two common approaches to O-D control are discussed below.

2.4.1 Displacement-Adjusted Virtual Nesting

With Displacement Adjusted Virtual Nesting, or DAVN, the idea is to determine a value to the network of an ODF by considering its revenue contribution (the fare) minus any opportunity costs that are incurred by the potential displacement of a local passenger on the connecting leg. These displacement costs are estimated as follows. A network linear program is formulated to maximize revenue over the network, where the decision variables, x_j^k, are the number of seats to make available to itinerary j (where j may traverse one or more flight legs i) in fare class k. The demands, d_j^k, are assumed to be deterministic, and are set to the mean demand forecasts. The constraints require that the decision variables do not exceed the mean forecasted demands, and that the number of seats allocated per flight leg i does not exceed fight leg capacity C_i. The shadow prices, SP_i, associated with the leg capacity constraints provide a value for occupying the last seat on the flight leg. Note that if the mean demand forecast is below capacity, then the shadow price will be zero.

Booking limits for ODFs are determined at the flight leg level by considering the total fare of the ODF and subtracting from it the shadow prices on the other flight legs traversed by the itinerary. A local ODF will be placed in a revenue bucket corresponding to its total fare, as will an ODF for which the shadow prices on the connecting flight legs are zero. However, if a shadow price on a connecting flight leg is greater than zero, then the network value of an ODF will be smaller than its total fare, and may be placed in a lower revenue bucket. The booking limits on the virtual buckets are determined according to the EMSR heuristic, and a booking request is accepted if the bucket, into which the ODF falls, is open. Stated another way, the ODF revenue, F_j^k, less the sum of the shadow prices on the remaining connecting flight legs, $\sum_{i\in j} SP_i$, must exceed the minimum of the lowest open bucket B_{min} as follows.

$$F_j^k - \sum_i SP_i \geq B_{min} \tag{2.3}$$

DAVN is quite a robust network RM method because it uses multiple fare level ranges to determine booking availability; therefore, its results are less sensitive to small variability in historical input data or demand forecasting methods. One main weakness of DAVN is that its network optimizer treats demand as deterministic, although information about the probability distribution of demand is accounted for through the application of EMSR to find virtual bucket booking limits.

Value Bucket	Fare Range	Booking Class *(minus Displacement Cost)*	Values
1	500+	Connecting Class 1 DEN-FRA (– displacement cost on ORD-FRA leg)	700 – **100** = 600
2	300-500	Connecting Class 2 DEN-FRA (– displacement cost on ORD-FRA)	450 – **100** = 350
3	200-300	Local Class 1 DEN-ORD	250
		Connecting Class 3 DEN-FRA (– displacement cost on ORD-FRA)	375 – **100** = 275
4	100-200	Local Class 2 DEN-ORD	175
Etc.	<100	Local Class 3 DEN-ORD	95

Figure 2-6: Illustration of DAVN Virtual Bucketing with \$100 Displacement Cost on ORD-FRA Connecting Leg

2.4.2 Probabilistic Bid Price

Probabilistic bid price (ProBP) is a network RM method developed by Bratu (1998) that relies exclusively on forecasts at the OD fare class level, optimizes over the entire network, and does not use booking limits but rather bid prices as the booking control mechanism. The idea behind the ProBP algorithm is to determine the bid price, or network value of an available seat on a flight leg, using a prorated fare convergence technique. The OD fares of connecting itineraries are prorated to the flight legs they traverse according to the ratio of the EMRSc values of the affected legs, thus taking into account the stochasticity of the demand forecasts. The first step uses the forecasted demand and total OD fares for itinerary j (which uses leg i) as input, denoted F_j, to find EMSRc values on each flight leg. The prorated fares, denoted $PR_{j,i}$, which are used as fare input to the algorithm in subsequent steps, are then determined as follows.

$$PR_{j,i} = \frac{EMSRc_i * F_j}{\sum_{i \in j} EMSRc_i} \tag{2.4}$$

If the EMSRc values for any leg are found to be zero, then $PR_{j,i} = \frac{F_j}{|j|}$, where $|j|$ is the cardinality of itinerary j. An illustration of the ProBP algorithm process is provided in Figure 2-7.

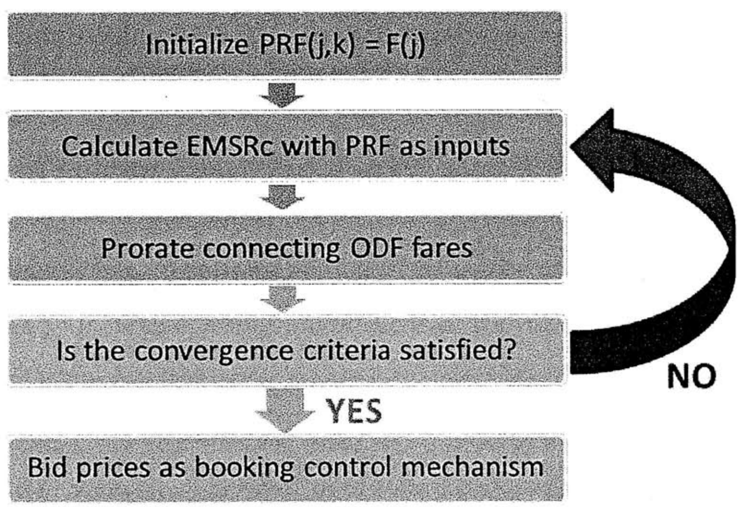

Figure 2-7: ProBP Algorithm, Adapted from Bratu (1998)

Because no booking limits are explicitly set, so long as the ProBP bid price equation is satisfied, the number of itineraries that can be booked at a fare level is unlimited. In actuality, the value of the remaining seats on the network changes with every booking that occurs, and the optimal approach would require recalculating the bid prices after every accepted booking. This weakness of the bid price mechanism requires that the bid prices be re-calculated very frequently (for example, every night). Also, because of relying on OD fare class forecasts, the demand forecasts for an OD pair in a given class may be very close to zero with high variation. The ProBP algorithm appears to be sensitive to the accuracy of demand inputs as well, as compared with the robustness of the DAVN bucketing approach, but its performance improves with higher demand and more accurate forecasts.

A summary of the levels (leg-based or network-based) at which the key elements in RM (forecasting, optimization, booking control) take place for the four RM methods described is provided in Table 2.1.

RM System	Level of Forecasting	Level of Optimization	Level of Control	Control Mechanism
Leg EMSRb	Leg Forecasts	Leg Optimization	Leg-based Control	Booking Limits
HBP	Leg Forecasts	Leg Optimization	Path-based Control	Bid Prices (EMSRc adjusted for local displacement)
DAVN	Path Forecasts	Network Optimization, Leg Capacity Constraints	Leg-based Control	Booking Limits
ProBP	Path Forecasts	Network Optimization	Path-based Control	Bid Prices (Converged prorated fares)

Table 2.1: Comparison of Levels (Leg- or Network-Based) of Forecasting, Optimization, and Booking Control, Adapted from Dar (2006)

2.5 Alliance Revenue Management

Although there is much research on the economic impacts of and motivation for airline alliances, the research on revenue management in airline alliances is not extensive, but has been increasing in recent years. Very little work has addressed the challenges, practical, technological, and legal, of implementing some of the proposed schemes in existing alliances. There are also very few studies of the willingness of airlines to cooperate in their revenue management because of the risk that the individual airline's revenues may not be maximized and the reluctance of airlines' RM departments to cede control. In addition, there is also some work on interline cooperation in cargo transportation (Houghtalen et al. (2011), Agarwal and Ergun (2008) and Agarwal et al. (2009)), but the main differences from the passenger airline sector are that demands for cargo transportation are realized before routing decisions and revenue sharing is determined, allowing the use of deterministic models to, for example, find dual prices for the partner's capacity.

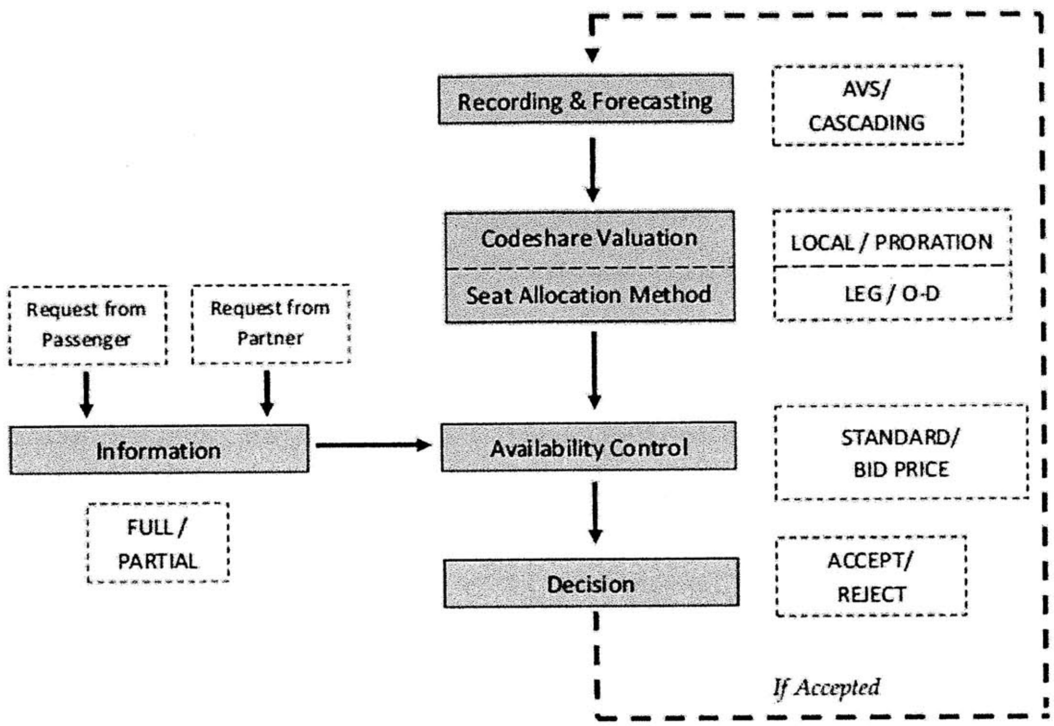

Figure 2-8: The Components of Alliance Revenue Management, Adapted from Jain (2011)

Figure 2-8 illustrates the steps in revenue management for airline alliances. As illustrated in Figure 2-8, the step of associating a valuation with the code share ODF comes before the seat allocation step where booking availability is determined. After all the revenues are collected, they must be allocated between the partners, which is referred to as revenue "resolution" or "sharing". The operating carrier is paid a "transfer price" for the use of each seat on his operated flight legs (his capacity). If each carrier values the code share itinerary according to the actual revenue he receives for use of his seat inventory (equal to the transfer price for the operating carrier, and to the fare minus the transfer price for the marketing carrier), then the revenue resolution amount is determined by the valuation. In that case, the revenue resolution and the code share availability control problems are the same. If the transfer price is different from the valuation, then the goals of solving these two problems differ. The aim of solving the booking availability control problem should be to maximize the joint alliance revenues, and the goal of the revenue resolution problem should be to prevent losses to any individual airline and ensure a fair split of the revenues.

This thesis focuses on the coordination of code share booking availability decisions among the alliance partners and assumes that revenue resolution has been previously decided in a manner deemed fair by the partners. However, this section does review cases in the relevant literature where the resolution and availability control decisions are intertwined.

The components of alliance RM in airlines are briefly described below and the assumptions used in this thesis are stated. For more information on the implementation details of alliance revenue management in practice, good overviews can be found in Jain (2011) and Vinod (2004).

Sub-Optimality of Alliance OD Revenue Management

Due to the presence of code share traffic, alliance revenue gains from using OD seat allocation can be sub-optimal. This is because each partner optimizes revenues over its own network according to its own RM system, and the resulting seat availability for code share flights may not maximize alliance revenues, and may instead result in cooperative or non-cooperative equilibria between the partners. This is exacerbated because code share itineraries often involve long-haul international legs with high revenue contribution. Attempts to quantify this revenue gap due to the presence of code share traffic (Jain, 2011; Wright, 2010; Graf, 2011) have found that the gap depends heavily on the characteristics of the particular network.

Although research in the field of operations research has attempted to address the problem of alliance revenue management and propose optimal solutions, these proposed approaches assume prerequisites that include having full information of the state of the partner's system, recorded booking histories and forecasts, infinite computation time, and having the technical capability, antitrust immunity, and willingness despite competitive concerns to share this information (see Wright et al. (2010) and

Topaloglu (2012)).

2.5.1 Recording and Forecasting of Code Share Bookings

When recording and forecasting the demand for code share itineraries, better revenues can be obtained if the historical database can distinguish code share bookings from locals, as shown in Jain (2011). In that case, full information is needed from the booking agent, such as a Global Distribution System (GDS). In this thesis, we assume that the alliance partners use cascading, which records the full itinerary and allows distinguishing code share from local bookings in the historical database, as opposed to AVS, which only sends messages about the availability status of certain classes on a flight leg to the partner. For more information on cascading, and the alternative AVS, which does not allow distinguishing the full O-D of code share bookings, refer to Jain (2011).

2.5.2 Valuation

Alliance revenues depend on the sale of own local and connecting itineraries as well as code share itineraries. In turn, the availability of code share itineraries depends on the revenue value of the code share demand that is provided as input to the seat allocator. This value is not in question for own locals and connecting itineraries, where the contribution to the airline's revenues is simply equal to the fare for the itinerary. In the case of code share itineraries, while it is clear that the revenue gain to the alliance as a whole is equal to the code share fare, the question arises of how much revenue contribution a code share booking provides to the individual airline. For example, for an individual airline using DAVN, assigning a revenue value equal to the total fare of the code share would place it in a high revenue bucket and result in very good booking availability, increasing the chance that a seat is booked by a code share passenger rather than a local passenger. Two valuation options, static valuation, which remains the same throughout the booking process, and dynamic valuation, which changes over time depending on the system parameters, are discussed below.

Static Valuation

With a valuation that is static, or remains constant over the booking horizon, the possibilities include using the total fare of the code share itinerary, the local fare of the partner's own traversed flight leg (both total and local valuation can overvalue the code share itineraries), or a proration of the total fare. Proration can be done, for example, according to the ratio of the mileage traversed by the flight legs, or according to the ratio of the highest local fares on the flight legs.

ORD $\rightarrow$ FRA $\rightarrow$ BUD

Booking (O-D)	Marketing Airline	O-D Fare	Bid Price at Time t
ORD-FRA	UA	\$ 200	\$ 250
FRA-BUD	LH	\$ 500	\$ 300
ORD-BUD	Codeshare (UA/LH)	\$ 600	

Local

Airline	Valuation of ORD-BUD
P1	\$ 200
P2	\$ 500
Total	\$ 700

Prorated

Airline	Valuation of ORD-BUD
P1	\$ 150
P2	\$ 450
Total	\$ 600

Dynamic

Airline	Valuation of ORD-BUD
P1	(600-300)=\$ 300
P2	(600-250)=\$ 350
Total	\$ 650

Figure 2-9: Illustration of Code Share Valuation in RM Optimizer, Adapted from Jain (2011)

Note that, in Figure 2-9, the sum of local values assigned to code share flight legs exceeds the code share fare, effectively overvaluing the code share itinerary. In a network where code share paths have high network value, this can increase revenues. In this thesis, we use local valuation, as representative of current airline practices. Also, it was shown in simulations in Jain (2011) that results achieved using local valuation can exceed those of using prorated values, despite the fact that local valuation overvalues the code share itinerary's network contribution (the transfer price is usually a prorate of the total fare, less than the local fare).

Darot (2001) argues that overvaluing code share itineraries can reduce availability for own locals and connections, and in turn, can reduce local and connecting revenues. Therefore, the individual airline should avoid potentially harming its own revenues that are not subject to revenue sharing agreements and value code shares according to their contribution to the own airline. However, this approach may not maximize revenues for the alliance, instead resulting in a non-cooperative equilibrium. It is also worth noting that the bookings of own local and connecting itineraries has an effect on the alliance partner that is not accounted for if the alliances perform separate optimization. This effect can be seen as an opportunity cost to the partner (or change in the partner's expected revenues) due to the removal of an airline's own seat inventory that could have been used for code share bookings later on. For the derivation of this opportunity cost in an alliance airline's value function using Bellman equations, see Wright et al. (2010).

Dynamic Valuation

Jain (2011) proposes and tests a scheme called dynamic valuation, where the input to the optimizer is the total code share fare minus the partner's bid price from the previous optimization (or time period). Figure 2-9 also provides an example of dynamic valuation. The results are very encouraging and show revenue gains near to those of BPS for code share availability control (expained in the next section) in DAVN, and much better results in ProBP (about a .25% revenue gain for DAVN and ProBP). It is argued that improved performance of ProBP under dynamic valuation is a result of the sensitivity of the ProBP optimization to fare inputs. This thesis continues the examination of dynamic valuation in the same and a different network setting, with the exchange of current (not dated) bid prices and more frequent optimization (calculation of bid prices and bookings limits) from that used by Jain, with results presented in Chapters 4 and 5.

Wright et al. (2010) model a Markov game of perfect information, where each partner knows the other's value function, and the functions are identical. The value functions take the form of Bellman equations derived using a dynamic programming formulation of airline revenues during the time horizons of the booking process. Their aim is to examine the proportion of "first best" revenues (the maximum revenues that the alliance could earn as one airline) that can be attained by the partners under various transfer price schemes, with the valuation of the code share itinerary equal to the transfer price. They examine static (prorated) and 3 different dynamic pricing schemes (bid prices, bid price ratios, and "partner prices" named by operating carriers). In their analysis, the transfer price is the same as the code share valuation, treating the two problems of alliance revenue management and resolution as identical. Their findings show that the performance of static schemes is nearly as good as the best dynamic schemes (achieving about 90% of first best revenues), but that static schemes do not adjust well as network parameters change, which could rapidly reduce revenues. Some dynamic schemes perform very well, and are able to adjust to changing network parameters. However, their performance deteriorates if partners post transfer prices to maximize their own revenues (for example, sending incorrect bid prices or naming transfer prices that are too high), and this risk is acknowledged by the authors.

It should be noted that the results obtained in Wright et al. (2010) are based on simulations in a network consisting of just two flight legs with ten seats each, in which the proportion of code share itineraries was varied. The authors acknowledge that the computational complexity of finding the set of transfer prices is much too great to apply their model to networks of realistic size, and that heuristic or approximation approaches need to be developed.

2.5.3 Code Share Availability Control

Availability control refers to the step of accepting or rejecting a code share booking request, and includes direct availability control by the marketing carrier and bid price sharing control. With standard control by the marking carrier at local valuation, code shares are treated as own local bookings and their booking availability is determined during seat allocation. With bid price sharing, the partners share bid prices (or DAVN network displacement costs, or EMSRc values) for their own operated legs on the code share itinerary and attempt to make informed accept/reject decisions to benefit the alliance. Details regarding bid price sharing with single/dual airline control are presented in Chapter 3. In the following two subsections, we describe two code share availability control options, one where only the marketing partner is responsible for the availability control of code share itineraries, and one where code share availability control depends on both airline partners.

Direct Control by the Marketing Airline

Direct control refers to the case where the marketing carrier is responsible for deciding whether to make a code share itinerary available for sale. This type of control determines availability of code share itineraries at the same time as local and connecting itineraries. Accepting a code share booking will require receiving an AVS message from the partner that the code share ODF is also available in the partner's system. It treats code share itineraries either as part of the forecast for locals or separately from locals, with their corresponding valuation (prorated, local, dynamic) used as the fare input to the optimizer.

An option that could achieve optimal joint revenues, suggested by both Boyd (1998) and Vinod (2004), is to exchange seats among the alliance partners until the relative values of the seats to each airline's network are equal. After the seats are exchanged and paid for among the carriers, each airline has individual control over the seats by his own RM system. Boyd formulated this proposition in terms of marginal seat values, and Vinod in terms of bid prices, but the idea is the same. In the proposed scenario, the resource allocation is optimal and expected revenue for the alliance can be maximized. However, in practice, airlines do not calculate bid prices or expected seat revenues for seats on flights that they do not operate, as they do not have access to the booking histories and forecasts for those non-operated flights. Significant technological changes to the airlines' RM systems and antitrust immunity may be required before such a scheme could be implemented.

Applying finance theory, Graf and Kimms (2011) propose an options-based approach to capacity control on a single flight leg, where the marketing carrier can purchase options from the operating carrier for the right to buy seat inventory in the future at a pre-determined strike price. They allow for dynamic inventory adjustment through the buy-back of inventory by the marketing carrier as demand is realized during the booking process. Their model takes the options and strike prices as given parameters, it does not consider network effects, and the authors acknowledge that searching through the entire solution space for the optimal values of these prices would be very time-consuming. In further work in her dissertation, Graf (2011) presents and tests a fast-performing heuristic that allows applying the options-based approach for determining the capacity controls within feasible calculation times. No theoretical basis or evidence is presented that this scheme performs better than the other methods proposed in the literature.

Topaloglu (2012) develops a deterministic LP model inspired by Williamson (1992)'s, similar to the approach of DAVN. The LP is solved over the joint alliance network, and then the constraints linking the partners' decisions to the joint alliance network solution are relaxed through the dual prices, thus decomposing the problem into smaller problems by airline. Autonomous direct control policies for each individual airline are extracted from the results with valuation and revenue sharing according to the dual prices. The author acknowledges that application of this methodology would require airlines to truthfully share information about their pricing, demand forecasts and remaining capacity, the legal and technical capability to do so, and the willingness to cede some autonomy to a central planner. The need for methods for implementing this truthful exchange is stressed.

Bid Price Sharing Control

In most revenue management systems, there exist estimated values of unsold seats, which are loosely referred to as bid prices, but can take of the form of EMSRc values, shadow prices, or prorated bid prices, as discussed earlier in this chapter. Under bid price sharing (BPS) control, a code share itinerary is accepted if the fare exceeds the sum of the bid prices (of the partners operating the various flight legs) on all the legs traversed. A schematic of the BPS process is presented in Figure 2-10.

It was proposed in Darot (2001) that airlines exchange either actual bid prices (if they have the legal ability to do so), or to infer bid prices from the lowest available fares, an idea re-iterated in Vinod (2004), in order to inform one another of the value of seat inventory on code share flight legs. Bid price inference may be a feasible option for airlines that do not have the antitrust immunity to share such information.

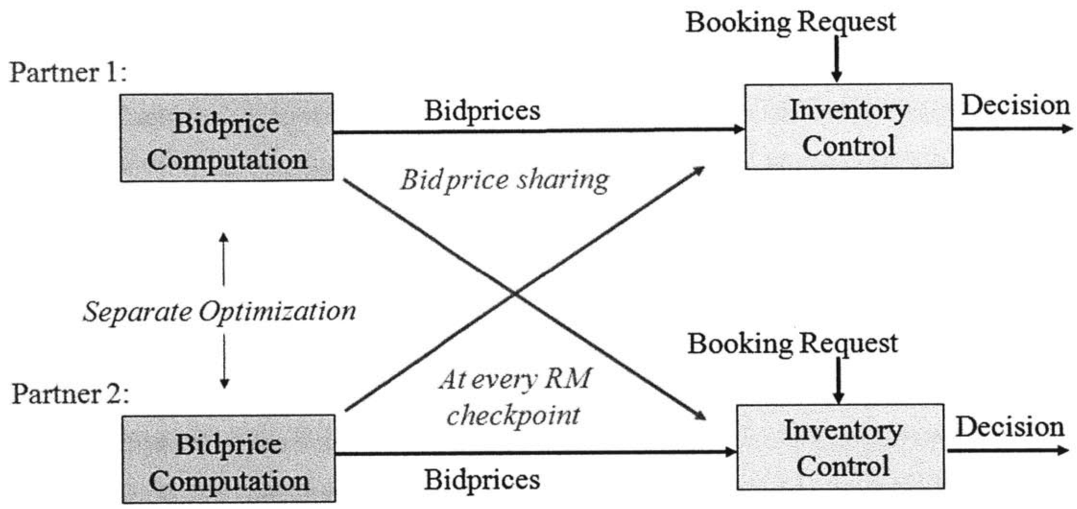

Figure 2-10: Illustration of Bid Price Sharing for Code Share Availability (Darot, 2001)

Jain showed that, when both partners use a version of DAVN, sharing bid (shadow) prices from the previous optimization, dated by as much as one week, still produces revenue gains of up to 0.27%. However, the results of BPS when the partners used ProBP only provided revenue gains of up to .05%. These results were obtained in a 44-city hypothetical network where code share fares were very high relative to local and connecting fares, with an average network load factor (LF) of 83%, where one alliance competed with two other non-allied airlines, and where all four airlines were located in the US with flight legs emanating toward the east and west. This thesis continues to test BPS in the same and in a different network setting, exchanging current (not dated) bid prices with more frequent optimization from that used by Jain, with results presented in Chapters 4 and 5.

In his dissertation, Wright et al. (2010) offers another version of the alliance problem. He proposes a game of incomplete information, where the carriers ignore the second-order effects on the partner of selling own inventory (i.e., do not account for opportunity costs to the partner of selling own local and connecting tickets in their value function). In the incomplete information game, partners also exchange bid prices for code share availability control. The small-scale simulations in Wright et al. (2010) show that bid price control produces gains just as good as those of the dynamic transfer price schemes in the cooperative game of complete information. Wright's encouraging result indicates that the simpler BPS approach, which requires much less computation than the dynamic programming approach with transfer prices but produces similar revenues, may be a good solution to the alliance RM problem.

2.5.4 Revenue Resolution

Revenue resolution contracts typically require sharing revenue according to a prorated fare approach (Vinod, 2005). The contracts are established before code share availability control is exercised, but the revenue exchange occurs after tickets have been sold and money collected by the marketing carrier. IATA agreements require revenue sharing according to a prorate based on mileage, weighted more heavily on short-haul routes (which have a higher unit operating cost than long-haul routes). Such contracts, based on a fixed proportion, are referred to as special prorate agreements (SPAs) between two carriers, and they do not necessarily ensure that the operating carrier receives an amount larger than his bid price or expected marginal revenue for the seat that is sold. In a case where the operating carrier receives a transfer price less than the estimated value of his seat inventory, he will not wish to give up the seat for the benefit of the alliance.

Vinod (2004) extends bid price sharing beyond availability control, arguing that it can be used to improve the fairness of revenue sharing, so that airlines are incentivized to make better availability choices for the alliance. He proposes a dynamic proration scheme that, like in bid price sharing control, accepts a code share booking if its fare exceeds the sum of both partners' bid prices, and then pays the operating carrier at least his bid price if the SPA does not provide an amount in excess of the bid price. He admits that the implementation of this idea would be challenging, as airlines are still struggling with static proration and availability control of interline itineraries. Neither does he address the issue of asymmetric bid prices calculated by different means, which can result in very different bid price values. Vinod also discusses how dynamic revenue sharing can be tracked through the passenger name record (PNR) of a booking. At the event of each booking, the dynamic transfer price can be noted in the PNR for later use in revenue resolution.

The availability and revenue from local and connecting bookings is also affected by the presence of code share bookings, but this own local and connecting revenue is not shared. For example, the idea that a carrier might include an opportunity cost to his partner of selling own local and connecting itineraries does not make sense in a non-cooperative game, because such an approach reduces the availability of own inventory in favor of code shares. This presents an issue when determining a contract for sharing revenues from code share bookings according to a pre-fixed amount. Under such a contract, the aim will be to maximize revenue from local and connecting bookings and reduce revenue from code shares, as argued by Darot (2001). It is likely that the effect on airline behavior of this aspect of the non-cooperation game, where players aim to maximize their own revenue, may not be negligible, necessitating very careful negotiation of revenue sharing contracts.

2.6 Summary

In this chapter, airline and alliance revenue management were reviewed. The concepts of differential pricing and fare structures were explained. Methods tested in this thesis for forecasting and unconstraining closed booking observations were presented. Leg- and network-based revenue management methods used for determining seat allocation tested in this thesis (EMSRb, HBP, DAVN, and ProBP) were compared.

The second part of the chapter focused on the challenges of alliance revenue management and revenue resolution. The steps of alliance revenue management, beginning with the recording and forecasting of code share bookings, were described. It was explained that the valuation of code share bookings, which can be static or dynamic, may or may not correspond to the transfer price paid to the operating carrier for use of its seat inventory. The determination of seat availability for code share itineraries may be done in a decentralized manner, directly by the marketing partner, or using BPS to better coordinate decisions by accounting for the total opportunity cost to the alliance of using seat inventory. Lastly, revenue resolution among the alliance partners was discussed.

Some of the alliance RM-related literature reviewed in this chapter presents interesting ideas and novel approaches for the solution of the alliance revenue management problem, but makes assumptions about the technical, legal, and cooperative environments of airline alliances that are currently untrue and unrealistic for the foreseeable future. This thesis aims to present feasible solutions for alliance booking availability control that can be implemented within the next few years given the current operating conditions and technical capabilities of airlines.

Chapter 3

Methodology

In this chapter, an overview of the experimental methodology used in the thesis is outlined. We first describe PODS, the software simulation tool used to test the various alliance revenue management techniques. The inputs, passenger simulation, forecasting, and simulation properties are discussed. We then introduce the two PODS alliance networks tested in this research: the US-based alliance network A4 and the trans-Atlantic network E. The types of bid prices that can be exchanged among the alliance airlines are compared in the context of bid price sharing (BPS). The mechanism of BPS for code share availability control is defined for the revenue management methods tested. Lastly, an example is provided to illustrate single versus dual airline availability control for code share booking requests, and the timeliness of bid price exchange is discussed.

3.1 Passenger Origin-Destination Simulator

The experiments in this thesis used a software simulation called The Passenger Origin-Destination Simulator (PODS) to test the effects of sharing information among alliance partners. PODS was developed at The Boeing Company in 1997 by Hopperstad, Berge and Filipowski (Hopperstad, 2005). PODS comprises two underlying models that represent the processes of passenger choice and airline revenue management systems. An illustration of the PODS processes and the interaction of the two comprising models is presented in Figure 3-1.

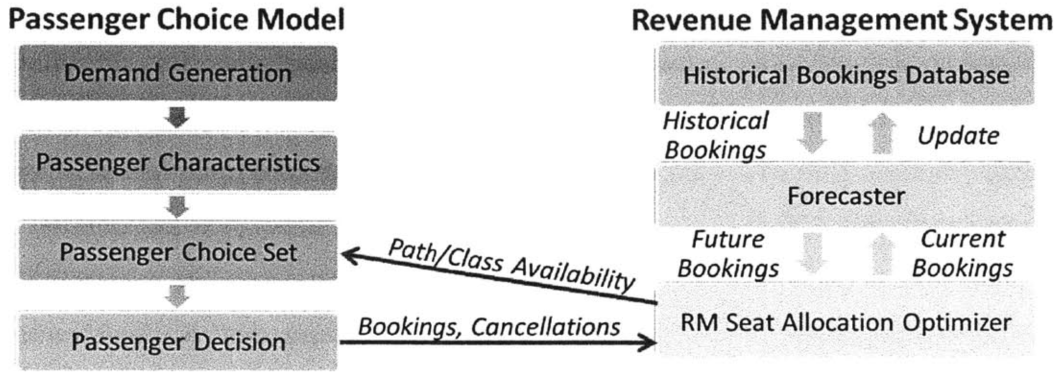

Figure 3-1: Illustration of PODS Processes, Adapted from Belobaba (2010)

The passengers are presented with itinerary choices made available for booking by the airline revenue management systems, and the passenger decisions are recorded by the RM systems' databases. Thus, the two basic models in PODS interact at the levels of seat allocation and passenger choice/decision (Belobaba, 2010). PODS is the most sophisticated competitive airline simulator tool known to the author. It has extensive modeling capabilities, including passenger preference and decision making, competitive interaction between airlines with overlapping networks, and different demand forecasting methods and revenue management systems among the competing airlines.

3.1.1 Inputs to PODS

The user provides inputs to the simulator that are based on assumptions about passenger characteristics in air transportation. The inputs include the proportions of business and leisure passengers by O-D market, as well as the arrival rates of these passengers during the booking process. For example, it is generally true that leisure passengers arrive earlier in the booking process and have a lower willingness-to-pay (WTP) for their tickets, a lower disutility associated with ticket restrictions, and less sensitivity to timing of flight departure, arrival, and connecting itineraries. Business passengers typically arrival later in the booking process and are more sensitive to ticket restrictions and flight timing. Passengers who arrive later in the booking process, on average, have a higher WTP, and capitalizing on this fact in the seat allocation decisions is often instrumental in improving revenues.

Inputs relating to the airlines and their revenue management systems include the revenue management schemes used by airlines in the simulation, the number of fare classes and the restrictions on each fare class, advance purchase requirements on each fare class, and the fares associated with each O-D itinerary and fare class. Also, each hypothetical PODS network includes a variety of cities served by each airline, departure times for scheduled flights between cities, and various aircraft sizes assigned to each flight leg.

3.1.2 Simulation of Passengers

Passengers are generated according to the input business/leisure mix, with a maximum WTP that is modeled by a negative exponential distribution, thus capturing the smaller proportion of passengers who are willing to pay 4 or 5 times the lowest existing fare in the market (base fare). The simulated passengers have a desire to travel from origin to destination with a preferred time window for their departure and arrival times. Disutility costs for the average business or leisure passenger are obtained by associating a monetary penalty with any fare restrictions (such as cancel or change fees, or minimum stay requirements), connecting itineraries, unfavorite airlines, and replanning (if no itinerary is feasible within the preferred time window and WTP). These monetary costs are randomized according to Gaussian distributions to model the stochasticity in passenger preference. The sum of these disutility costs is added to the actual fare of an itinerary to obtain its total generalized cost, and the passenger chooses the option with the lowest total cost. If there is no itinerary whose fare falls below the passenger's maximum WTP threshold, then the passenger does not fly.

3.1.3 Forecasting of Future Demand

PODS also provides each airline with a forecaster that uses data from the airline's historical database to forecast future demand by fare class at either the flight-leg or itinerary level. Because the recorded bookings do not reflect actual demand by WTP or passenger type, but rather only contain the fare class in which the passenger was booked, there will be a downward bias in the forecasts for the demand for the top fare classes. Since passengers will book the cheapest fare available, the airline does not observe their true WTP. If standard forecasting methods (such as pick-up) are used, as described in Chapter 2, the forecaster will in turn forecast more demand for the lower classes and less for top classes, and this phenomenon is is referred to as spiral down (for more information, see Cleaz-Savoyen, 2005). It is commonly observed in PODS that more aggressive forecasting and seat allocation methods (those that protect more seats for top classes) result in better revenue performance because they mitigate the effects of spiral down, particularly in less-restricted fare structures. We will see in Chapters 4 and 5 that aggressive seat protections may improve revenues, but this depends on the competitive situation, demand, and passenger preferences faced by the airline.

3.1.4 Simulation Properties

The booking process is simulated over 63 days prior to flight departure, divided into 16 time frames (TFs). At user-specified time intervals (i.e., once per time frame or each day) the booking limits (and bid prices, shadow prices, and EMSRc values, if applicable) are re-calculated by each airline's revenue management system. However, fare classes may be closed within a TF if the maximum booking limit has been reached. Each simulated airline has access to its own historical database only.

Each simulation trial consists of 600 samples, which each represent one day of booking behavior. The first 200 samples are discarded to allow convergence to an equilibrium state without the influence of initial conditions. The remaining 400 samples are then averaged to obtain the simulation trial output. Averaging the sample results ensures small standard deviation of the results, which consist of reported revenues, load factors, yields, fare class mix, and many other details for each airline. For the tests of alliance scenarios, 2 trials were used per run. The software is currently used by the PODS Research Consortium at MIT to test the effects of different revenue management techniques on airlines.

3.2 Alliance Networks Used in PODS

In this section, the two alliance networks used in the simulation for testing the effects of BPS are described. The fundamental structure of the networks is different, and thus it is expected that the results from bid price sharing will differ.

3.2.1 US-Based Network A4

A network structure and schedule of flights must be provided as input to PODS. For the first part of the results section of this thesis (Chapter 4) we use PODS alliance network A4, used in Jain (2011). Network A4 has 40 spoke cities, resulting in 444 flight legs and 572 O-D markets. The network has four competing airlines, all of which have hubs based in the central area of the United States, with airlines 2 and 4 forming an alliance. Airline 1 competes with the alliance on all routes and represents a strong network carrier. Airline 3 is a smaller airline that represents a low-cost carrier and competes in 296 markets with a cheaper and less restricted fare structure. In addition to operating code share flights into each others' hubs, airline 2 serves four international cities in the east and airline 4 serves six international cities in the west. There is thus a natural asymmetry between the alliance airlines, which is the case in reality and has not been represented in the OR literature on alliances. An illustration of network A4 is provided in Figure 3-2 below.

In the baseline case, airlines 2 and 4 use EMSRb (leg-based RM control) for seat allocation and standard availability control. In the results section, all reference to changes from the baseline case refer to the scenario where the alliance airlines use EMSRb with leg forecasting and local valuation of code share itineraries. Airline 1 uses DAVN with 8 virtual buckets and itinerary-specific forecasting. Airline 3 uses a simple revenue management technique that does not require forecasting called Adaptive Threshold with a target load factor of 90%. A summary of the baseline case for network A4 is provided in Table 3.1 below.

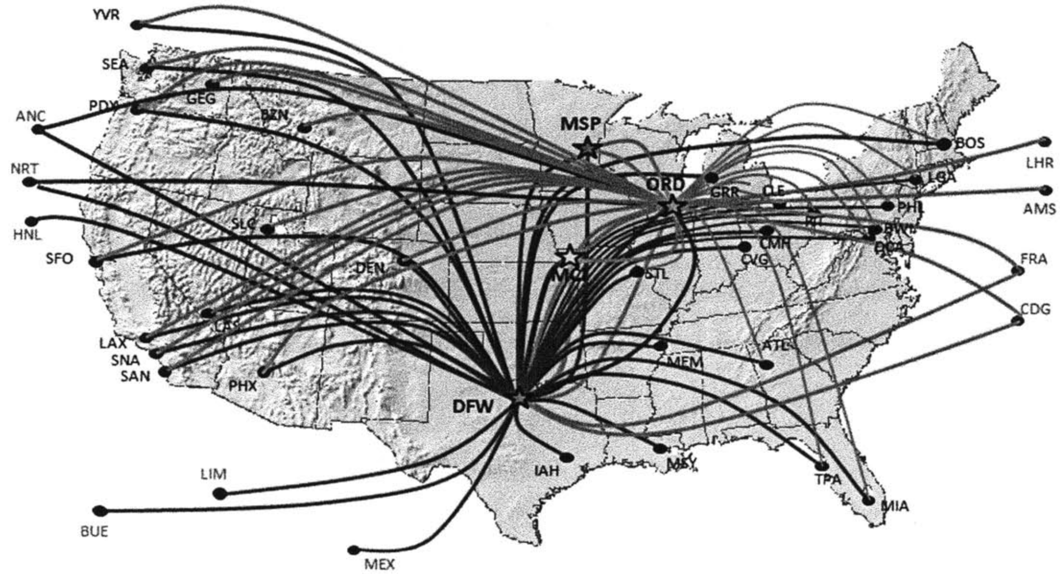

Figure 3-2: Illustration of Alliance Network A4 (airline 2 routes in orange, airline 4 routes in dark blue)

Airline	RM Method	Forecasting
AL 1	DAVN (8 virtual buckets, leg-specific)	Path/Class
AL2	EMSRb	Leg/Class
AL3	Adaptive Threshold ~90% LF	N/A
AL4	EMSRb	Leg/Class

Table 3.1: Summary of Baseline Case in Network A4, from Jain (2011)

3.2.2 Trans-Atlantic Network E

Network E represents two competing alliances, each with partner hubs across the Atlantic. The two competing alliances have one set of partners (airlines 1 and 2) whose hubs are located in the central United States, while the other two partners (airlines 3 and 4) have hubs located in Europe. Airlines 1 and 3 form alliance 1, and airlines 2 and 4 make up alliance 2. The spoke cities emanate from the continental hubs, with 10 in the northern part and 10 in the southern part of Europe, as well as 10 in the western part and 10 in the eastern part of the United States. In the baseline case for network E, all airlines use EMSRb with leg forecasting.

Roughly speaking, network E has a dumbbell structure, as compared to network A4's butterfly structure. The hub-to-hub trunk routes (served by large aircraft) carry a large amount of passengers across the Atlantic into the hubs and feed the smaller hub-to-spoke routes (served by small aircraft). Such trunk flights occur three times a day, providing connecting opportunities during three banks. The routes are served by each airline, resulting in a total of six hub-to-hub flights and 12 additional trans-Atlantic flights per bank. In addition, some local and connecting traffic does not cross the Atlantic, but traverses spoke-to-hub and hub-to-spoke routes, staying on the same continent. Also, there are hub-bypass routes crossing the Atlantic that go from a continental hub to a major city on the other continent, without requiring a connection at the partner hub.

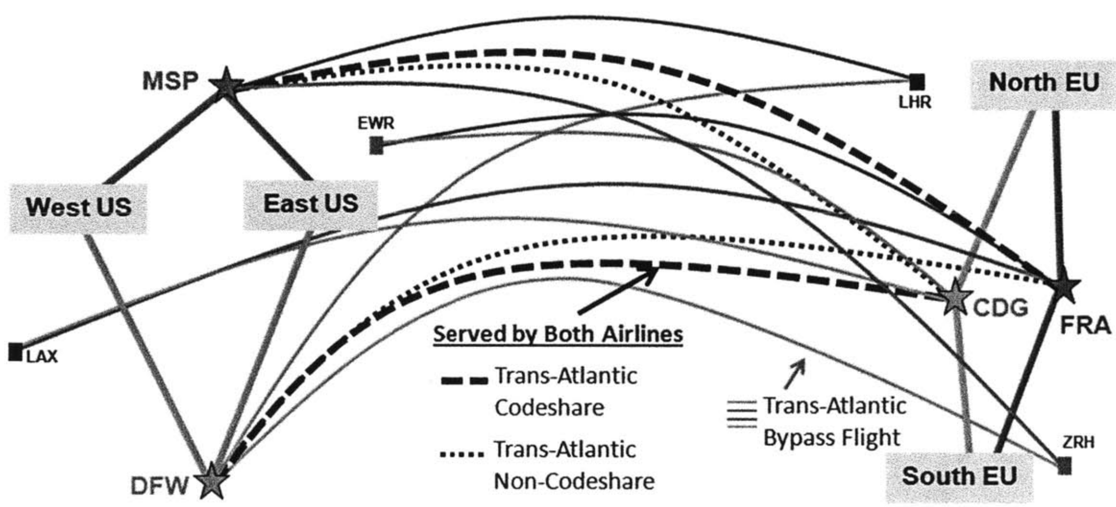

Figure 3-3: Schematic of Network E

3.3 Types of Bid Prices

In Chapter 2, the idea of bid price sharing was introduced from the prior literature on alliance revenue management for controlling code share availability. Several ways of estimating the value of unused flight leg seat inventory, which we loosely refer to as "bid prices", were presented in the context of the revenue management methods that produce them. These included the prorated bid prices of the ProBP algorithm, the shadow prices of DAVN, and the critical expected marginal seat revenues (EMSRc) of the EMSR heuristic. In this section, we compare the calculation, values, strengths, and weaknesses of these bid prices.

When an alliance partner uses ProBP, the value that represents the opportunity costs of selling a seat on a flight leg is the prorated bid price calculated by the ProBP algorithm. As discussed in Chapter 2, the values represent a prorated portion of expected marginal seat revenues that have been calculated iteratively, after accounting for the forecasted demand for all possible connecting itineraries that could use a seat on all flight legs in the airline's own network. The airline ships the ProBP bid price as its estimate of the value of a seat on a code share leg. However, this value may not be the best representation of the value of the seat on the code share flight leg to the combined alliance network because the calculation was performed without the ProBP algorithm's access to the partner's information during the optimization.

With DAVN, the dual solution to a network linear program (subject to capacity constraints and deterministic demand forecasts) produces shadow prices for each leg of an airline's own network. These shadow prices represent a network displacement cost and are used to adjust for the displacement of local passengers on connecting itineraries. Because these values are shadow prices and represent a penalty for violating the capacity constraint on a flight leg, these values are zero if the forecasted demand is below the capacity. The problem with using shadow prices from deterministic demand forecasts is that they do not account for the probability that demand takes a value larger or smaller than the mean forecast, and in that case, the capacity constraint may or may not be violated. A single shadow price does not reflect this probability.

Another alternative for DAVN airlines is to ship the critical EMSR value for a flight leg, which represents the estimated value of the last available seat given remaining capacity, based on virtual bucket demand forecasts. These values are higher than shadow prices on average because they account for the probability that demand will be higher than the mean forecast and are especially high later in the booking period when high WTP passengers are expected to arrive into the booking process.

For a visual representation of how these bid prices change over the course of the booking process, the average values of the three types of bid prices from scenarios in network A4, where the alliance airlines both used either ProBP or DAVN as their RM methods, are graphed by time frame in Figure 3-4 below. We can see that the average ProBP bid prices are higher throughout the booking process than are DAVN network shadow prices, and that EMSRc values are highest of all throughout, gaining especially in the later time frames, as the remaining capacity decreases. Average shadow prices are lowest because of the presence of many zero values for flights whose average demand forecast is below capacity. Their values also peak in later time frames and fall very quickly at the end as demand for some flights does not materialize, and the number of flights with demand forecasted to exceed capacity diminishes.

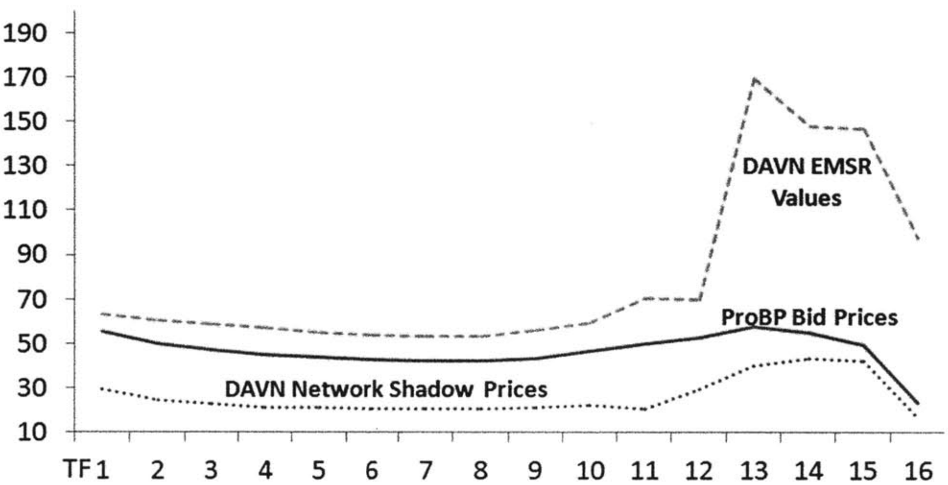

Figure 3-4: Graph of Average ProBP Bid Prices, DAVN Shadow Prices, and EMSRc Values by Time Frame

3.4 BPS for Availability Control

BPS, introduced in Chapter 2, is the mechanism of alliance partners sharing opportunity costs or network displacement costs of unsold seats on their flight legs to better inform code share availability decisions. Using the definitions in Jain (2011) for consistency with that work, the total code share O-D fare, F_{CS}, less the the most recently received alliance partner's bid price P_{part}^{t-1}, lagged by one time frame or day (or some amount of time lag), must exceed or equal the bid price (or seat value) on the operating partner's flight P_{own}^{t}, as follows:

$$F_{CS} - P_{part}^{t-1} \geq P_{own}^{t} \tag{3.1}$$

The important thing to note with regard to BPS is that the bid prices are calculated independently by each partner, using only the information in that partner's historical database. Partners do not have access to each others' booking databases, forecasts, or optimizers. Also, note that since each partner runs his optimization software separately, booking limits on local and connecting itineraries are established prior to BPS. This can produce sub-optimal booking protections on local and connecting itineraries as well as code shares because the optimization did not use all the available information when determining local and connecting protections. Bid prices are then sent to the partner after this separate optimization, and code share acceptance policies are applied in the last step of alliance revenue management (code share availability control), as illustrated in Figure 2-8 of Chapter 2.

3.4.1 ProBP

When the alliance partners use ProBP, the bid price sharing is simple, and works just like availability control of connecting itineraries in ProBP. The partner's most recent shipped bid price (a small lag in the timing of shipment is indicated by $t-1$) represents his estimated value of the marginal seat of inventory on his flight leg. The marketing partner (or own airline) has access to its most recently calculated bid price, indicated by t. In order for the code share itinerary to be made available for booking, the code share fare, F_{CS}, must exceed the sum of the own bid price on the marketing carrier's affected flight leg and the partner's affected flight leg, as in equation 3.2

$$F_{CS} \geq BP_{own}^{t} + BP_{part}^{t-1} \tag{3.2}$$

3.4.2 DAVN with Shadow Price Exchange

When the partners use DAVN and exchange shadow prices, equation 3.2 must be modified. The bid price shipped by the partner is now the shadow price, SP_{part}^{t-1}, from the dual solution of the network LP in DAVN. Recall that these shadow prices will frequently be zeros if the forecasted demand for the flight leg is below capacity. The "bid price" used by the marketing partner is B_{min}^{t}, the minimum range of the lowest currently open DAVN virtual bucket for the code share flight leg, instead of the prorated ProBP bid price.

$$F_{CS} \geq B_{min}^{t} + SP_{part}^{t-1} \tag{3.3}$$

Note that if the operating partner's shipped shadow price is zero, this will result in a code share itinerary being made available if the total fare falls into an open virtual bucket on the marketing partner's affected flight leg.

3.4.3 DAVN with EMSRc Value Exchange

Another alternative for a value to use in BPS among DAVN partners is to ship own EMSRc values from the virtual buckets for the seats on flights involved in code share itineraries. Note that EMSRc values are higher than shadow prices, because they are less likely to be zero as are the shadow prices from the deterministic LP dual solution. Thus, using EMSRc values as bid prices will typically be more restrictive for code share availability, as it requires that the code share fare be higher in order to satisfy the BPS equation.

$$F_{CS} \geq B_{min}^{t} + EMSRc_{part}^{t-1} \tag{3.4}$$

A comparison of the acceptance criteria for ProBP versus DAVN BPS scenarios is provided in Figure 3-5 below.

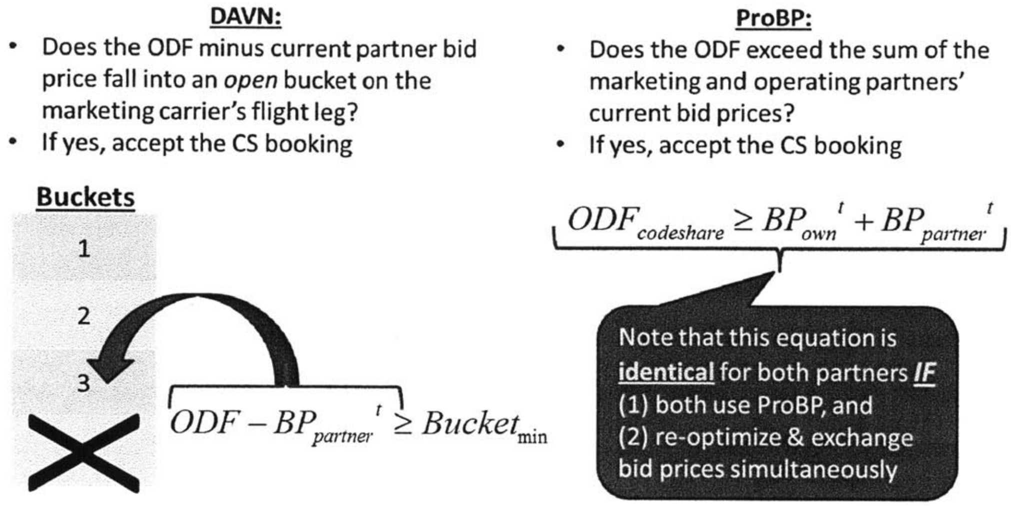

Figure 3-5: Bid Price Sharing for Code Share Availability in ProBP and DAVN

3.4.4 HBP and EMSRb

When using HBP or EMSRb, which are leg RM methods, as described in Chapter 2, a partner only has EMSR values for all of its flight legs. By default, this becomes the bid price that is shipped. For code share availability control with BPS, the HBP partner uses the HBP equation, simply using the bid price received from his partner as the second bid price value. Of the two opportunity costs in his possession, his own EMSR value and partner's shipped bid price, the lower value is multiplied by the displacement factor, d, to account for the probability of displacing two local passengers on the code share itinerary. The displacement factor used in the experiments in this thesis is .25, assuming a .50 change of displacing a local passenger on either flight leg. The availability control equation is thus:

$$F_{CS} \geq Max(EMSR^{t}_{own}, P^{t-1}_{part}) + d * Min(EMSR^{t}_{own}, P^{t-1}_{part}) \tag{3.5}$$

With EMSRb, the availability control is on the leg level, so it is not possible for a partner to perform any code share availability control separate from the leg level. The leg protections for code share itineraries will have been determined during the seat allocation step, and the only way to modify the resulting protections is though either changing the valuation associated with code shares (which is set to local valuation in this thesis), or by modifying the forecasts. However, bid price sharing is still possible when an EMSRb partner is involved, as long as the other partner uses some form of O-D control. The EMSRb partner would ship the EMSR values for his flight legs, and the O-D partner will use those values as bid prices for code share control.

3.5 Examples of Code Share Availability Control

In dual availability control, both of the partners' availability control equations must be satisfied. In single availability control, the partners ship each other their respective bid prices as before, but only the marketing carrier is responsible for making the availability decision. Therefore, when a booking request is being made, only one airline must process the availability control equation and produce a decision, and the information technology burden is greatly reduced. However, single control can produce asymmetric sales of code share itineraries if the sets of bid prices used in availability decisions by each partner differ. The more dated the exchanged bid prices are, the more the sets of bid prices used to satisfy the above equations may differ. If both partner use ProBP and exchange bid prices at the same time, the acceptance equations will be identical. A summary of the acceptance criteria for code share booking control using single or dual control and ProBP or DAVN is provided in Table 3.2 below.

3.5.1 Standard Code Share Availability Control Example

An example of code share availability control is provided now, as it occurs in the three possibilities of: 1) during the seat allocation step (assuming the partners have the right to free sale as long as the fare class is open on the partner's flight leg), 2) BPS with single airline availability control, and 3) BPS with dual availability control.

Suppose both airlines use ProBP bid price control as their optimization method to determine seat protections. Airline 1 has calculated its leg 1 bid prices to be as follows. The last calculation shipped to airline 2 was $P_{A1}^{t-1} = 150$, and the current

Accept/reject criteria for code share itineraries

"Bid price" sent by partner	**Single Control** ODF Available on Marketing Partner [mkt]	**Dual Control** ODF ALSO Available on Operating Partner [op]
ProBP Bid Price	$ODF_{codeshare} \geq BP_{mkt} + BP_{op}$	$ODF_{codeshare} \geq BP_{op} + BP_{mkt}$
DAVN Shadow Price (SP)	$ODF_{codeshare} - SP_{op} \geq Bucket\_min_{mkt}$	$ODF_{codeshare} - SP_{mkt} \geq Bucket\_min_{op}$
DAVN EMSRc Value	$ODF_{codeshare} - EMSRc_{op} \geq Bucket\_min_{mkt}$	$ODF_{codeshare} - EMSRc_{mkt} \geq Bucket\_min_{op}$

Same Equations!

Different Equations!

Table 3.2: Single or Dual Code Share Availability Control with ProBP and DAVN

bid price for own use is $P^t_{A1} = 190$. Airline 2 has calculated its leg 2 bid prices to be as follows. The last calculation shipped to airline 1 was $P^{t-1}_{A2} = 120$, and the current bid price for own use is $P^t_{A2} = 140$. Therefore, the total bid price sums used for code share availability control with bid price sharing are:

$$Airline\ 1 : P^t_{A1} = 140 + t - 1_{A2} = 190 + 120 = 310 \tag{3.6}$$

$$Airline\ 2 : P^t_{A2} = 140 + t - 1_{A1} = 140 + 150 = 290 \tag{3.7}$$

If the airlines do not use bid price sharing as a post-fact control method for code share availability, then the results from the seat allocation step are the default availabilities from the RM optimizer. In the example illustrated below, leg 2 in class 4 is not available (operated by airline 2) because the local fare (100) is less than the current bid price (140). In order for a code share itinerary to be available for sale, both legs must be available on each airline partner. Thus, in this example, the code share path is not available for sale by either airline (even though leg 1 in class 4 is available on airline 1).

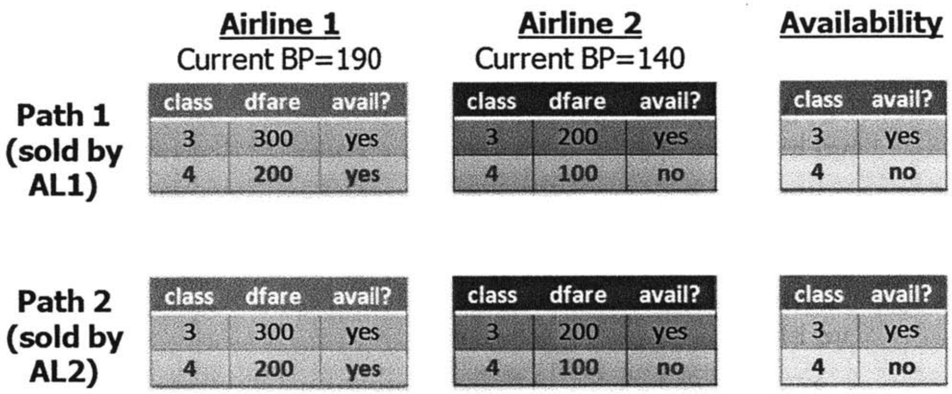

Figure 3-6: Illustration of Code Share Availability Control without Bid Price Sharing

3.5.2 BPS Dual Availability Control Example

When the airlines use dual availability control with bid price sharing, the decision fare is no longer the local fare, but rather the total code share fare (in this case, 300). For airline 1, the sum of the bid prices for class 4 (310) is greater than decision fare (300) for the code share path traversing leg 1, so code share leg 1 is not available. However, on airline 2, the bid price (290) is less than the decision fare (300), and code share leg 2 is available on airline 2. However, because dual control requires that both partners have the itinerary available, neither airline sells the code share itinerary.

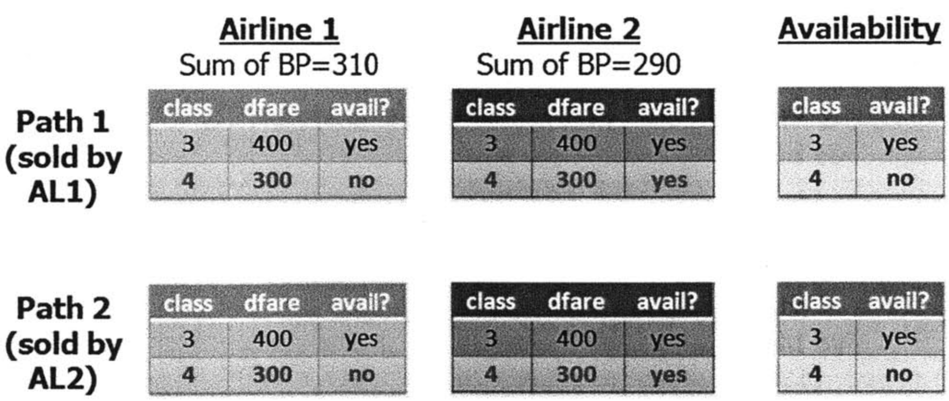

Figure 3-7: Bid Price Sharing with Dual Partner Code Share Availability Control

3.5.3 BPS Single Availability Control Example

With single availability control, the alliance partner may sell the itinerary as long as it is available according to the partner's own calculations. It is not required that the specific code share itinerary also be available on the partner airline. As before, for airline 1, the sum of the bid prices for class 4 (310) is greater than the decision fare (300) for the code share path, so the code share path is not sold by airline 1 However, on airline 2, the bid price sum (290) is less than code share fare (300). Unlike in dual control, however, the code share path is in fact sold by airline 2. Thus, single control results in more code share bookings sold than dual control, producing less strict control decisions and resulting in less aggressive revenue management.

Airline 1 Sum of BP=310 | **Airline 2** Sum of BP=290 | **Availability**

Path 1 (sold by AL1)

Airline 1:

class	dfare	avail?
3	400	yes
4	300	no

Availability:

class	avail?
3	yes
4	no

Path 2 (sold by AL2)

Airline 2:

class	dfare	avail?
3	400	yes
4	300	yes

Availability:

class	avail?
3	yes
4	yes

Figure 3-8: Bid Price Sharing with Single Partner Code Share Availability Control

3.6 Timeliness of Bid Price Exchange

In the equation 3.1, the partner's bid price is dated (it is from the prior time frame). The network displacement costs that are represented by the bid prices will be more accurate if the information is from the current time frame (or as recent as possible), and we expect that the revenue benefits to the alliance will be greater. However, sharing information in the current time frame requires more advanced RM system and communication technology on the part of the alliance members, and there exists a range of capabilities among airlines today, with some near real-time communication in place among parent airlines and their subsidiaries, and more rudimentary communication between other alliance partners.

Note that when ProBP is used and bid prices are exchanged and recalculated at the start of each day, which was tested and verified in the experiments in this thesis, the resulting availability control decisions with single and dual availability control are identical. This is because both partners' equations are identical when the bid prices each partner uses are identical.

3.7 Summary

This chapter described the methodology to be used in the thesis experiments. First, PODS was described, along with the inputs to the underlying models, simulation of passengers and simulation properties. Then, the two alliance networks used in the thesis experiments were presented. The types of bid prices available for exchange in BPS for code share availability control were compared and contrasted. Finally, BPS with single versus dual availability control was explained, and an example was provided.

In the following chapters, the results of tests on the performance of BPS with single and dual airline control with local valuation of code share paths, and dynamic valuation (explained in Chapter 2) of code share paths, are presented for various optimization frequency, load factor, RM method, and network scenarios. Chapter 4 continues the work of Jain (2011), presenting the results in network A4 of exchanging current bid prices, at 83% load factor, with two optimization frequencies and a variety of network and leg RM combinations for the alliance airlines. Chapter 5 presents the results in network E at 83% and 86% load factors, and two optimization frequencies, for each of the two competing alliances when both partners in an alliance use ProBP and DAVN. Chapter 6 presents the overall conclusions, discusses implications for airlines, and proposes areas for future research.

Chapter 4

Results in Network A4

In this chapter, an analysis of the results in the US-based PODS alliance network A4 (introduced in Chapter 3) is presented. First, some assumptions and methodological details are clarified. Details regarding the baseline case, where the two alliance airlines use EMSRb as their RM method, are then presented and discussed in the context of the network characteristics and their effect on code share traffic. The results when the alliance partners use ProBP, and then DAVN, with optimization occurring at the start of each of 16 times frames, as compared to daily, are presented. The performance of bid price sharing (BPS) and dynamic valuation (DV) in each of these network RM and optimization frequency scenarios is then analyzed. The last section of the chapter provides a summary of the results obtained when the alliance partners use various (symmetric and asymmetric) combinations of network and leg RM methods.

This chapter serves as a continuation of the work of Jain (2011) on BPS and DV in PODS alliance network A4. In particular, this chapter addresses several unanswered questions from the prior findings and revises several of the methodological assumptions in Jain (2011).

First, we modify the assumption that there is a time lag (of one time frame) in the exchange of bid prices among alliance partners. In the results of this thesis, all bid prices that are exchanged are the most current values, obtained from the most recent optimization of alliance partners, and available for use immediately by the receiving partner.

Second, we perform experiments to test the performance of BPS and DV as a function of the optimization frequency (and thus, the accuracy) of the bid prices received. The performance of network RM, as a function of bid prices (prorated EMSRc values in ProBP, and LP shadow prices in DAVN) and virtual bucket booking limits (calculated via EMSRb in DAVN), is affected by optimization frequency. In alliances, BPS and DV are further affected if dated (less accurate) bid prices are used.

In Jain (2011), the optimization frequency for DAVN was at the start of each of 16 times frames, and once every 200 bookings for ProBP. In the first two sections of this chapter, we will examine how BPS and DV in alliance network A4 react to optimization that occurs daily versus at the start of each of 16 time frames when the two alliance partners both use ProBP or DAVN. All results will be compared with the baseline case of the alliance airlines using EMSRb, and local valuation of code share paths.

Third, we use a different implementation of BPS in DAVN, which produces very different results for DAVN than observed in Jain (2011). In that work, the total code share fare, F_{CS}, must exceed the sum of the marketing partner's EMSRc value on its code share flight leg, $EMSRc^t_{own}$, and the partner's bid price from the prior time frame, BP^{t-1}_{part}, as follows: $F_{CS} \geq EMSRc^t_{own} + BP^{t-1}_{part}$.

This thesis's DAVN BPS implementation uses a bucketing criterion rather than an EMSRc criterion, meaning that the total code share fare minus the partner's current bid price must exceed the marketing partner's minimum open bucket value, B^t_{min}, on the code share flight leg. Presented in the same equation format as the EMSRc criterion used in Jain (2011), the criterion is as follows: $F_{CS} \geq B^t_{min} + BP^t_{part}$. The EMSRc criterion performs better because it is more aggressive, requiring that code share fares be higher in order to pass the acceptance criteria. However, bucketing is more consistent with DAVN treatment of own connecting itineraries.

Fourth, the DAVN BPS implementation in Jain (2011) also affected the availability of local and connecting itineraries. Rather than using local valuation of code shares during the determination of virtual bucket booking limits, $F_{CS} - BP_{part}$ was used as the valuation in calculating the virtual bucket booking limits according to EMSRb. This resulted in a larger demand forecast for the higher value virtual buckets, and therefore caused stricter booking limits on the lower virtual buckets. The result was a better overall performance of DAVN in local, connecting, and code share traffic components. Some of the positive effects of DV were achieved by this BPS implementation. However, such an implementation removes the separation between the optimization step (performed separately by each airline, before bid price exchange) and the post-fact code share availability determination, which is the intention of BPS. In this thesis, we use local valuation of code shares for the determination of virtual bucket booking limits according to EMSRb.

Lastly, we also test BPS with single airline code share availability control, whereas all results in Jain (2011) referencing BPS used dual airline code share control. Chapter 3 provided a detailed example of the difference between BPS with single and dual availability control.

Table 4.1 provides a summary of the important characteristics of the four airlines in alliance network A4 in the baseline case, including load factors, revenues, and traffic details, which will be useful later in understanding the results of BPS and DV in the network E experiments as well. Note that traffic (passengers carried) percentages include both own and partner code share passengers for each alliance airline, because code share passengers occupy seats on both airlines' flight legs. It is immediately clear that the code share passengers provide a high proportion of revenues relative to their proportion of traffic.

Airline-RM	% Load Factor	*Revenue (000s)*	% Local	% Connecting	% Code Share	*Passengers Carried*	% Local	% Connecting	% Code Share
1-DAVN	83.9	*3413*	28	72	-	*8656*	46	54	-
2-EMSRb	81.3	*2117*	32	39	28	*6505*	49	35	16
3-AT90	78.3	*876*	60	40	-	*5516*	63	37	-
4-EMSRb	83.9	*2562*	26	51	23	*7159*	38	47	15

Table 4.1: Baseline Characteristics of Network A4 by Airline

Table 4.2 provides a breakdown of the percentages of revenues and bookings generated by the three components, local, connecting, and code share, for the alliance as a whole in the baseline case when the alliance airlines both use EMRSb. Note that, in Table 4.2's presentation of alliance characteristics, code share booking percentages are only 8.4% because code share passengers are only counted once per itinerary, whereas in Table 4.1, code share passengers were counted twice, once per alliance partner. It is especially clear what an important revenue source the code share traffic is in network A4, since the average code share fare is nearly five times the average local fare and about three times the average connecting fare.

	% Bookings	% Revenue	Average Fare
Local	46.5	29.1	215
Connecting	45.1	45.7	347
Code Share	8.4	25.2	1022

Table 4.2: Total Alliance Baseline Revenue and Traffic Components

Now that we have introduced the chapter and presented some key aspects of network A4, we proceed to the results in ProBP, followed by DAVN. In the last section of the chapter, a summary table with results from different, asymmetric combinations of ProBP, DAVN, HBP and EMSRb for the two alliance airlines will be presented to obtain an overall picture of the performance of BPS and DV with various possible RM combinations among the alliance partners. The experimental results presented in the summary table will show results corresponding to TF optimization for DAVN and EMSRb, and optimization every 200 bookings for ProBP and HBP, to remain consistent with the results in Jain (2011). The end of the chapter presents conclusions regarding the results obtained in network A4.

4.1 ProBP

In this section, we present and discuss the results for the case where both airlines in the alliance use ProBP. Figure 4-1 shows the percent revenue gains over baseline obtained by the alliance when it uses ProBP, and additionally BPS or DV. The figure is divided into three groupings, with the first showing the results if optimization occurs at the start of each of 16 time frames, the second showing the results from optimization every 200 bookings, and the third, optimization at the start of each day. The middle grouping corresponds to the ProBP results found in Jain (2011). There is no distinction for BPS with single or dual availability control with ProBP because the simultaneous calculation and exchange of bid prices results in identical ProBP equations for code share acceptance criteria among both partners, thus producing the same results. Note that all figures show the total alliance changes (for both airlines taken together) from the baseline case where both alliance partners use EMSRb.

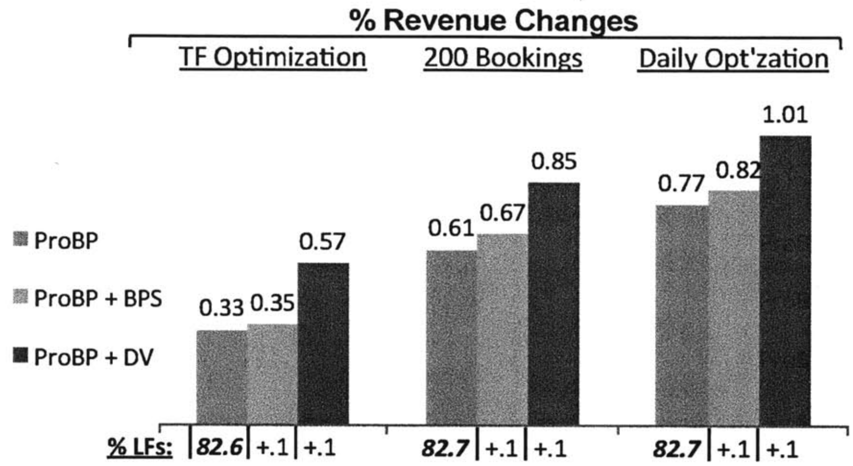

Figure 4-1: ProBP: Alliance Percent Change in Revenues over Baseline

Optimizing daily, rather than once each time frame (i.e., 4 times as often), results in large revenue gains of +.44%. The results shown here are consistent with the results of Jain (2011), in that when using ProBP, BPS gains minimally (up to .05%), and DV gains significantly (up to .24%). This result remains true regardless of the frequency of optimization. Figure 4-2 shows that the improvements in revenues from daily optimization are highest for the connections component. Daily optimization creates revenue gains in all traffic components by similar amounts for no BPS, BPS and DV. This indicates that the revenue improvements obtained from daily optimization are similar regardless of the alliance RM technique, whether BPS or DV. However, the revenue increase in the code share component, due to switching to daily optimization, is highest for BPS. Unlike BPS, DV has an indirect affect on other itineraries by increasing the bid prices on legs with heavy code share traffic, thereby displacing more connecting traffic than BPS, and thus earning less revenue in that component.

In Figure 4-2, we see that BPS results in gains in the code share revenues, but causes large falls in connecting, and marginal declines in the local revenues. On the other hand, DV generates even larger increases in code share revenues than BPS, as well as marginal gains in local revenues, thus offsetting the declines it causes in connecting revenues. DV causes the greatest losses in connecting revenues and traffic, though this traffic is not fully regained in local and code share components. The overall result is that the code share and local revenue gains of DV more than make up for the losses in connecting revenues, producing a +.24% increase in overall alliance revenues from ProBP with DV for all the optimization frequencies.

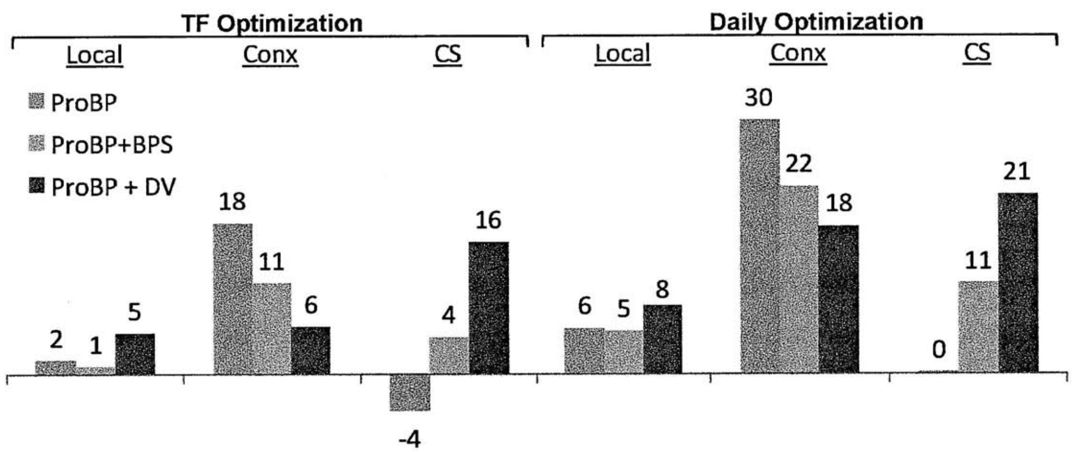

Figure 4-2: Change in Local, Connecting, and Code Share Revenues (000s)

Figure 4-3 shows that average bid prices decrease with daily optimization. Despite fewer bookings with DV, it actually raises bid prices because code share fares are very high value in network A4 relative to average fares for locals and connecting itineraries. The other two methods, no BPS and BPS, use local valuation of code share itineraries in the optimizer, which would shift bid prices downward. Looking at Table 4.3, there occurs an increase in average fares from daily optimization in all components, particularly in code shares (up to \$5) and about \$1 in locals and connections. DV and BPS both cause large increases in average code share fares. However, BPS also produces decreases in average connecting fares (and a small local fare increase as well) because of the decline in bid prices, which allows more own local and connecting bookings to be accepted at lower fares.

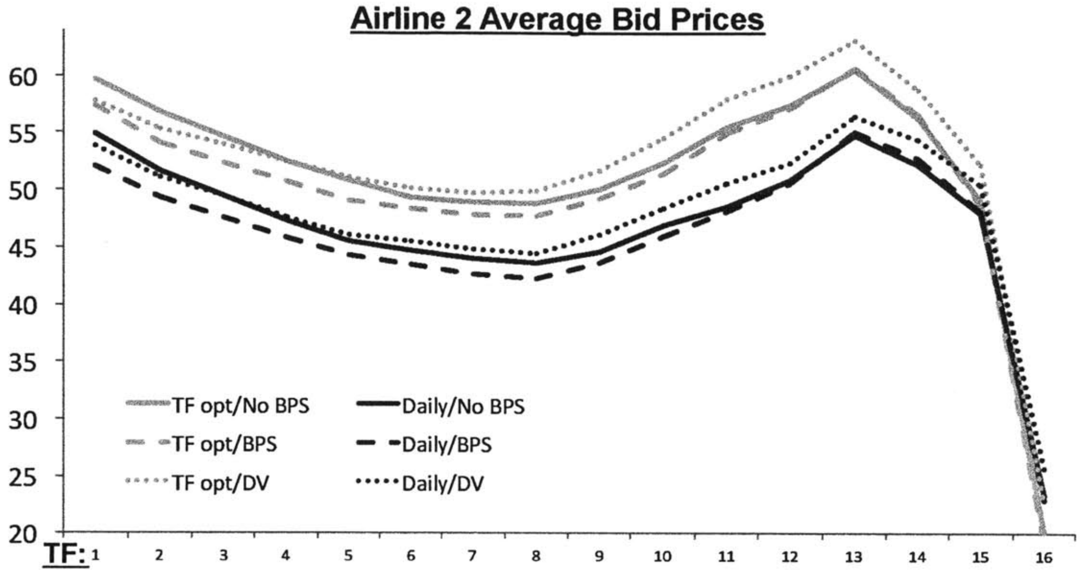

Figure 4-3: Airline 2 Average Bid Prices by Time Frame

	TF Optimization			Daily Optimization		
	No BPS	BPS	DV	No BPS	BPS	DV
Δ in Total Bookings	-35	-36	-52	-25	-24	-36
	Average Fares			**Average Fares**		
Local	-----------213-----------			-----------214-----------		
Connecting	354	353	354	355	-----354-----	
Code Share	1033	1046	1050	1038	1049	1052

Table 4.3: Change in Total Alliance Passengers (Compared to the Baseline Case Where Alliance Airlines use EMSRb) and Average Alliance Component Fares

Table 4.4 presents a detailed summary of the changes in local, connecting and code share component revenues, bookings, and average fares from the baseline case. Daily optimization (the three bottom shaded rows) accepts fewer local and more connecting bookings than TF optimization. Average bid prices are presented in Figure 4-3. Lower bid prices on some itineraries allow more connecting bookings to occur. DV, in turn, raises bid prices and reduces the number of connections to a large extent, a result that is not true for BPS. In fact, while more local, and the same number of connecting bookings are accepted using BPS, the revenues decline, as do the average fares.

The sizable decline in connecting revenues, but not a decline in passengers with

Change in	Optimization Frequency	Locals No BPS	Locals BPS	Locals DV	Connections No BPS	Connections BPS	Connections DV	Code Share No BPS	Code Share BPS	Code Share DV
Revenues (000s)	TF	2	1	5	18	11	6	-4	**4**	**16**
	Daily	*6*	*5*	*8*	*30*	*22*	*18*	*0*	***11***	***21***
Bookings	TF	51	57	60	-70	-71	-97	-16	-23	-15
	Daily	*43*	*47*	*48*	*-50*	*-51*	*-71*	*-18*	*-19*	*-13*
Average Fares	TF	-1	-2	-1	7	6	7	11	**24**	**27**
	Daily	*-1*	*-1*	*0*	*8*	*7*	*7*	***16***	***27***	***30***

Table 4.4: Summary Table of Changes in Local, Connecting and Code Share Component Revenues, Bookings, and Average Fares from Baseline

BPS, is in contrast to the decline in connecting revenues from DV that is accompanied by a decline in passengers, thus allowing more code share and local bookings. In addition, the code share revenues are not as high for BPS as for DV, but the number of code share passengers with BPS declines only slightly.

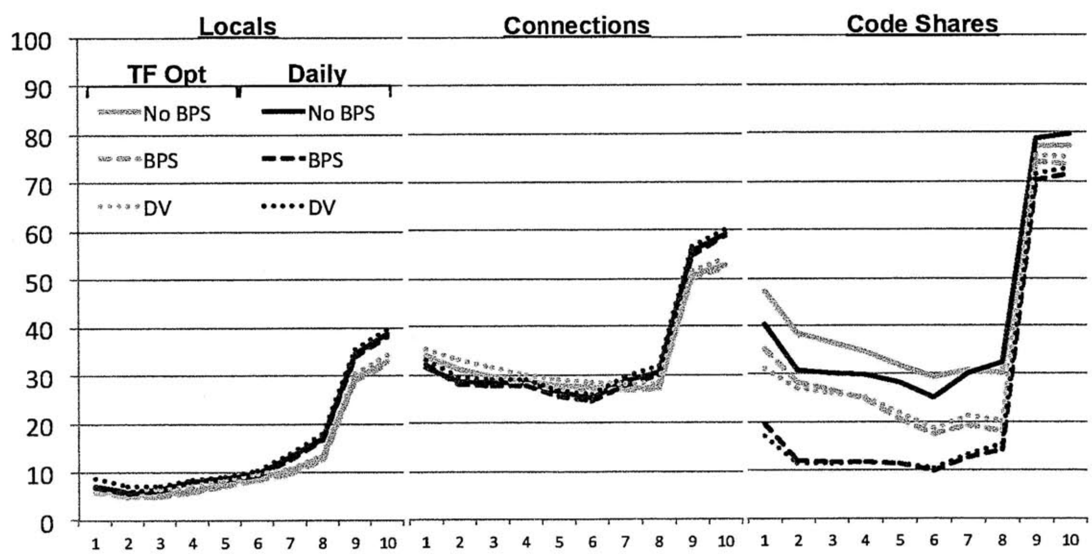

Figure 4-4: Airline 2 Local, Connecting, and Code Share Class 6 Closer Rates

Figure 4-4 shows the aggregate average closure rates of the lowest class (class 6) of airline 2 for the local, connecting, and code share traffic components. Daily optimization raises closure rates throughout the booking process for locals. For the connections and code share components, rates are lower in earlier TFs and then rise later on. Code share closure rates are much lower in early time frames with daily than TF optimization. Holding optimization frequency constant, there are nearly identical code share closure rates for code shares with BPS and DV, except that DV closures are marginally lower in early TFs and rise slightly above BPS in later time frames. This results in a large rise in code share revenues amid a small decline in code share passengers for DV. At the same time, revenues improve in the local component as well.

In general, the improvements of daily optimization occur due to higher closure rates in later time frames of all traffic components. DV raises bid prices on routes with heavy code share traffic, thereby generating slightly higher closure rates than BPS in all components.

4.2 DAVN

This section presents and discusses the results for the case where both alliance airlines use DAVN. Figure 4-5 presents the percent revenue gains over the baseline case (where both alliance airlines use EMSRb) obtained by the alliance when it uses DAVN, and additionally BPS (with single or dual airline availability control) or DV. The figure is divided into two sections, one for shadow price (SP) exchange, and the second for EMSRc value exchange, among the partners. There are two groupings in each section, the first showing the results if optimization occurs at the start of each of 16 time frames, the second showing the results from optimization at the start of each day. The first grouping in the first section corresponds to the results for DAVN in Jain (2011) (only the results for no BPS and DV). As mentioned at the start of the chapter, the implementation of BPS with DAVN differs in this thesis. The figure also presents an additional column for the results of BPS with single airline control, which was not present for ProBP.

The results indicate that DAVN is more robust than ProBP with less frequent optimization. Gains from TF optimization over baseline start out higher (+.57%) than the gains of ProBP (+.33%), but moving to daily optimization further improves revenues by +.22%., which is just half of the ProBP gain. As in ProBP the case, the

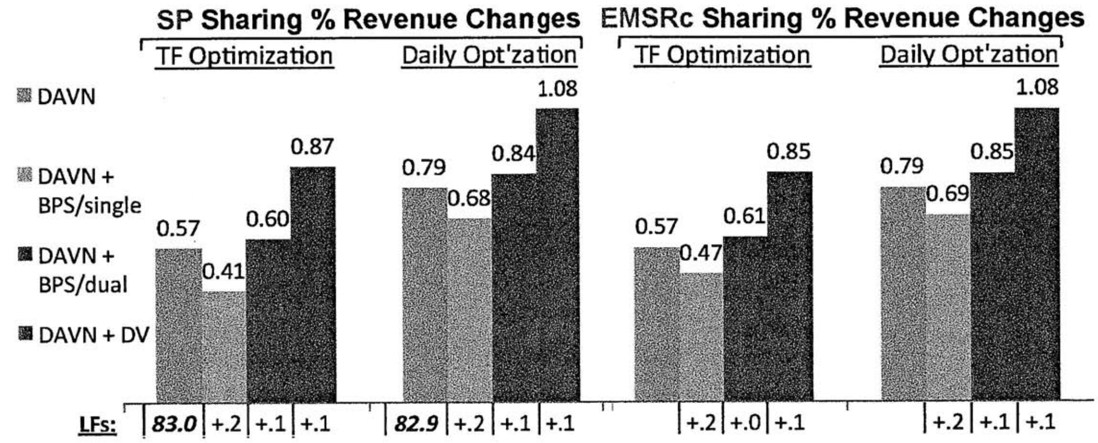

Figure 4-5: DAVN: Alliance Percent Change in Revenues over Baseline, and Load Factor Point Changes from Standard DAVN

additional gains from BPS and DV are consistent for each optimization frequency. Below the bars that show revenue gains are the network load factors for each network RM scenario without BPS, and the load factor point increase from applying BPS and DV. We can see that the load factors increase slightly for all BPS and DV scenarios, with the largest rise in load factors from BPS with single control, indicating that more miles are being flown by passengers in that scenario.

Of note is that the exchange of SPs or EMSRc values has little effect on the revenues. The revenue gains are slightly higher from EMSRc exchange and BPS with single control because EMSRc values tend to be higher, on average, than SPs. Thus, using EMSRc values as bid prices would result in a slightly stricter acceptance criteria (requiring the code share fare to be higher in order to accept the booking). However, this effect disappears if using BPS with dual control or DV. These results indicate that it is more important to exchange some form of bid prices, as long as they contain information about the value of a marginal seat on a flight leg, and that the specific form of the bid price is less important. For the subsequently presented data in this section, we focus on the SP exchange results.

Figure 4-6 shows that daily optimization (with SP exchange) creates revenue gains in all traffic components by similar amounts for no BPS, BPS and DV, as was true for

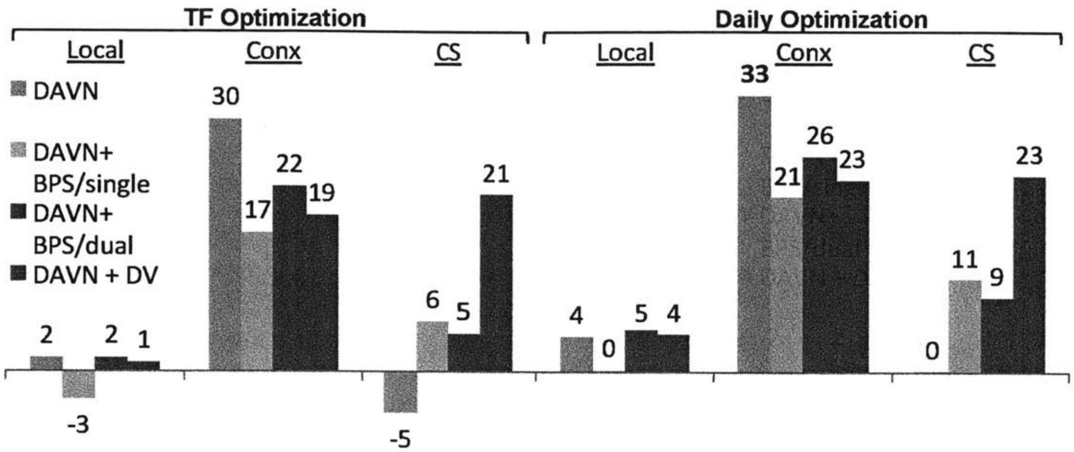

Figure 4-6: Change in Local, Connecting, and Code Share Revenues (000s)

ProBP. However, the gains are to a lesser degree than in ProBP, with the largest improvement due to daily optimization being in the code share and not the connecting segment (as was for ProBP). DV creates very high code share revenue gains in both cases, and BPS gains in the code share segment are similar for single and dual control (just slightly higher for single control). However, the difference in revenues between single and dual control is pronounced in the local and connecting components, where dual control performs consistently better than single control, and better than DV by a lesser margin. This trade off indicated that BPS with single control is accepting too many code share passengers at the expense of local and connecting passengers, with the modest code share revenue gains insufficient to make up for losses in local and connecting revenues.

Like for ProBP, Figure 4-7 shows that, although average shadow prices are about the same in early TFs, they decrease in later TFs with daily optimization. This results in the placement of more connecting fares into high-value virtual buckets, thus improving protections for the high fare bookings by closing down more low-revenue virtual value buckets. Additionally, we can see that DV causes decreases in the average shadow prices because total bookings decrease. With fewer flights predicted to exceed capacity, the deterministic LP produces more zero shadow prices, bringing down the average, additionally placing code share fares into high-value virtual buckets, and further increasing booking limits on low-value virtual buckets.

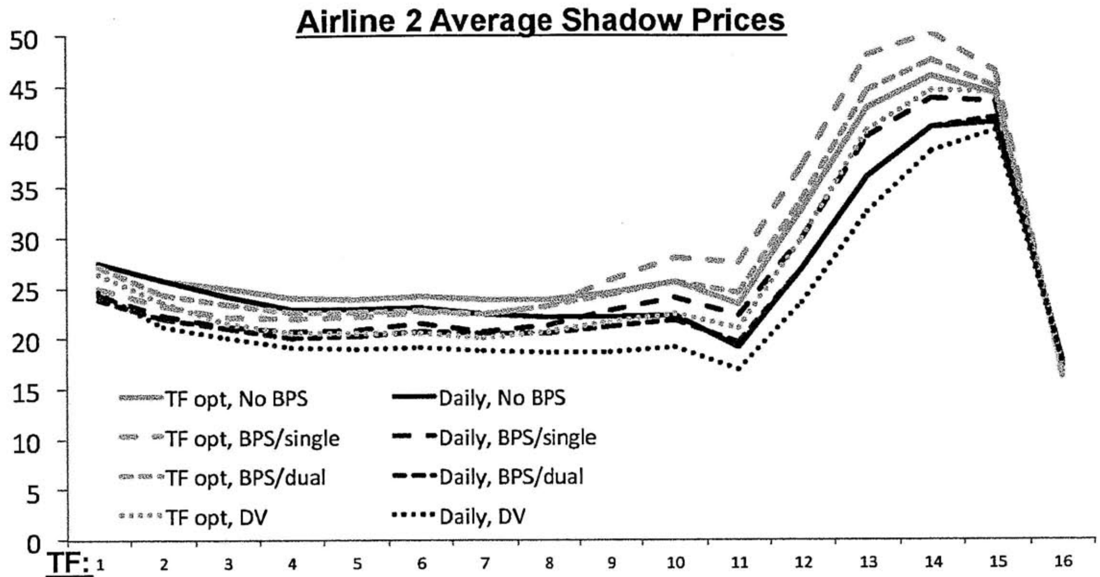

Figure 4-7: Airline 2 Average Shadow Prices by Time Frame

	TF Optimization				Daily Optimization			
	No BPS	BPS/single	BPS/dual	DV	No BPS	BPS/single	BPS/dual	DV
Δ in Total Bookings	-7	2	-5	-24	-7	2	-3	-26
	Average Alliance Fares				Average Alliance Fares			
Local	216	215	----216----		216	215	----216----	
Connecting	351	-------350--------			----352----		----351----	
Code Share	1023	989	1021	1031	1025	998	1027	1036

Table 4.5: Change in Total Alliance Passengers (Compared to the Baseline Case Where Alliance Airlines use EMSRb) and Average Alliance Component Fares

Table 4.5 shows that increases in average fares occur from daily optimization (+\$1-2) in connecting and code share components without the use of BPS or DV. If BPS and DV are in use, switching to daily optimization increases the average code share fares by \$5-9. Compared to no BPS, very large falls in average code share fares occur with BPS/single control, but there occur large rises in code share fares with DV. This indicates that BPS with single control accepts too many code share bookings at low fares than do any of the other methods, whereas DV results in more high-fare code share bookings.

Table 4.6 presents a summary of the changes in local, connecting and code share component revenues, bookings, and average fares from the baseline case. Daily optimization reduces the number of connecting bookings, but takes more locals (the opposite of the results for ProBP). Though daily optimization takes a few more code shares than TF optimization, applying BPS and DV reverses the effect and causes fewer code share bookings than TF optimization.

		Locals				**Connections**				**Code Share**			
Change in	**Optimization Frequency**	No BPS	BPS/ single	BPS/ dual	DV	No BPS	BPS/ single	BPS/ dual	DV	No BPS	BPS/ single	BPS/ dual	DV
Revenues (000s)	TF	2	-3	2	1	30	17	22	19	-5	6	5	21
	Daily	4	0	5	4	33	21	26	23	0	11	9	23
Bookings	TF	-25	-34	-21	-39	24	-9	10	4	-6	45	6	11
	Daily	-12	-20	-9	-26	8	-17	3	-6	-3	39	3	7
Average Fares	TF	1	1	1	2	4	3	3	3	1	-33	-1	9
	Daily	1	1	1	2	5	4	4	4	3	-24	5	14

Table 4.6: Summary Table of Changes in Local, Connecting and Code Share Component Revenues, Bookings, and Average Fares from Baseline

Looking at Figure 4-8, holding frequency of optimization constant, BPS with dual control and DV still result in very similar closure rates for code shares. The pattern of code share closure rates is the same for TF and daily optimization, only differing a little in magnitude, with daily optimization resulting in slightly lower closure rates. As expected, standard DAVN (no BPS) produces much higher closure rates than BPS or DV in the code share component. BPS with single control accepts more low fare passengers because it produces the lowest closure rates of any method, especially for code shares and connections in early TFs. DV produces marginally higher closure rates than BPS in all components, wherein lies its benefit.

We can see that, while code share and connecting closure rates change slightly with optimization frequency, local closure rates are the same at each optimization frequency, and rise with DV in each case, allowing room for code shares. Neither the optimization frequency nor BPS have an effect on local closure rates because local valuation is not affected by the calculated shadow prices, and BPS does not affect the virtual bucket booking limits as does DV. Code share itineraries are valued as

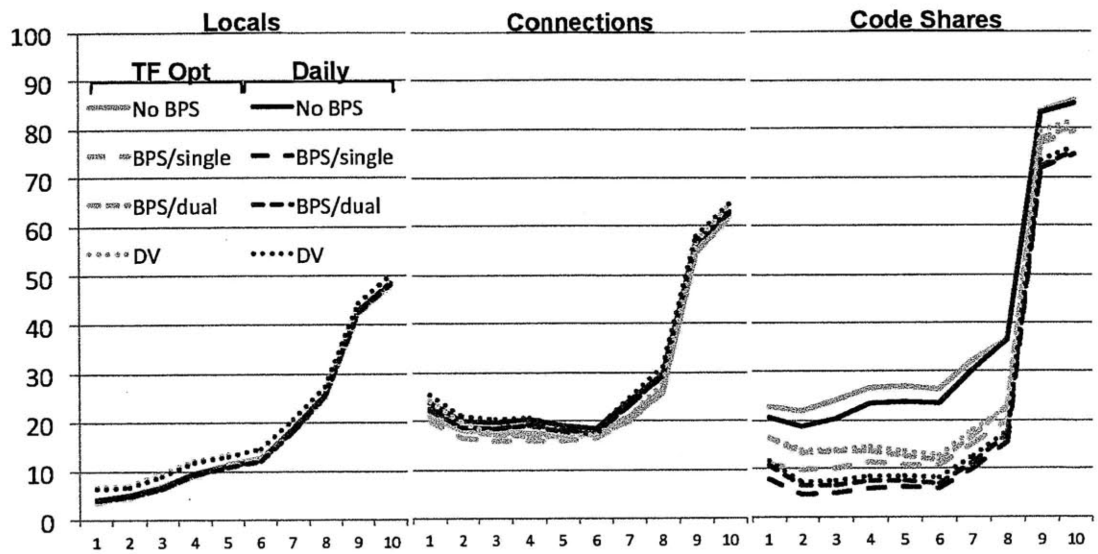

Figure 4-8: Local, Connecting, and Code Share Class 6 Closer Rates

locals with standard DAVN and with BPS, thus producing nearly identical local closure rates. On the other hand, DV increases the number of bookings predicted in higher value buckets, and thus increases the closure rates. In the case of connecting itineraries, the more accurate (and more frequently zero) shadow prices produce better booking limits on legs with high-value connecting itineraries.

4.3 Other Network and Leg RM Combinations

This section presents a summary of the results of different combinations of network with network RM, and network with leg RM. For consistency with the results in Jain (2011), the optimization frequency was kept at once per time frame for DAVN and EMSRb, and once every 200 bookings for ProBP and HBP. There are no DV results for the symmetric HBP scenario because HBP does not separate locals from code shares in its recording and forecasting, as it is based purely on leg forecasts and records code share bookings by leg and bucket. There are differences between the results of single and dual control for the ProBP and HBP cases because the optimization and BPS do not occur simultaneously (each airline can reach 200 bookings at different times from the partner). Note that the implementation of DAVN with BPS in this thesis differs from Jain (2011), as discussed in the beginning of the chapter. The implementation used here results in lower revenue benefits from BPS because the prior implementation obtained some of the positive effects of DV when calculating the virtual bucket booking limits. The first two columns of Table 4.7 show the results of the prior DAVN implementation for comparison.

% over Same RM (no BPS/DV)	Prior DAVN BPS Implementation		New BPS Results		Dynamic
Symmetric RM	**Single**	**Dual**	**Single**	**Dual**	**Valuation**
DAVN (SP Exchange)	0.14	0.29	-0.16	**0.03**	0.30
DAVN (EMSRc Exchange)	0.08	0.25	-0.10	**0.04**	0.28
ProBP*			0.00	**0.05**	0.24
HBP			0.05	**0.06**	N/A
Asymmetric Network RM					
DAVN/PROBP (SP Exchange)	0.08	0.17	-0.03	**0.05**	0.31
ProBP/HBP			0.02	**0.10**	0.15
Asymmetric Network/Leg RM					
DAVN/HBP	-0.01	0.17	-0.06	**0.09**	0.17
DAVN/EMSRb	-0.09	0.15	-0.20	**0.07**	0.16

*ProBP single control results differ from dual control because timing of bid price exchange is not simultaneous if optimization is based on booking count

Table 4.7: Benefits of BPS and DV with Various Network and Leg RM Combinations

It is clear that, in all cases, BPS with dual control produces marginal benefits (the bold column). BPS with single control often produces losses, especially if one of the airlines is using leg RM. At least some benefits may be obtained from BPS with dual control, more so in the case when one of the airlines is using some form of network RM, even with less frequent optimization. DV also produces consistently larger gains in revenue than BPS. This is because the valuation of code share itineraries is increased significantly due to their high network value in network A4, compared to the case where they are valued at the local fare.

4.4 Chapter Conclusions

With regard to the frequency of optimization as it relates to the performance of the two network RM methods, ProBP and DAVN, we have seen that increasing the frequency of optimization from occurring at the start of 16 TFs, to daily, helps ProBP (+.44%) much more than DAVN (+.22%). ProBP benefits more from the increased frequency of optimization because it does not have built-in booking limits the way that EMSRb or DAVN do, automatically shutting down a fare class once the limit is reached. So long as a booking fulfills the ProBP bid price equation, there is no limit to the number of bookings in a fare class that may be accepted until the next optimization occurs. In reality, the network value of a marginal seat on a flight leg changes with every incremental booking. Thus, more frequent updating of bid prices is especially important for bid price RM systems.

On the other hand, DAVN consists of several heuristics that create built-in robustness to inaccuracy, with revenue value ranges to define the virtual classes, and virtual class booking limits to prevent too many low fare bookings in between optimizations. Thus, it does not benefit as much as ProBP from increased frequency. Average shadow prices and their variances are found to decrease from daily optimization because estimates of the ratio of demand to remaining capacity are more accurate. Average bid prices in ProBP are also found to decrease. In ProBP, lower bid prices on legs with connecting traffic cause an increase in connecting traffic and revenue. For DAVN, the decrease in shadow prices results in the placement of connecting itineraries into higher value buckets, and stricter booking limits on lower value buckets (i.e., allowing fewer low-fare bookings), which results in more high-fare bookings in all traffic components. The result of more frequent optimization is a better fare class mix across all traffic components for both ProBP and DAVN.

It is clear from all of the experiments that BPS with single control is generally detrimental to revenues, regardless of the RM combinations used. In each case, BPS with single control is too permissive of accepting code share bookings compared to dual control, which has a more rigorous acceptance criteria by requiring that the availability equations of both airlines are satisfied. In addition, the permissiveness of BPS with single control also causes declines in local and connecting bookings and revenues, displacing those passengers by giving too much preference to code shares.

The gains from BPS with dual control (about +.05%) and DV (+.25-.30%) are similar for ProBP and DAVN, and consistent across optimization frequencies. DV increases ProBP bid prices because of the high value of code share itineraries in network A4, causing large code share and local revenue gains, but falls in connecting traffic and revenues due to displacement by code share and local passengers, which are found to be more beneficial to the network by the optimizer. The same is not true for BPS, where bid prices decrease in early time frames, and revenue gains are minimal.

In DAVN, BPS increases total traffic and thus shadow prices. However, unlike the ProBP bid prices, DV decreases DAVN shadow prices because of a decease in total traffic, causing more forecasts below capacity and more zero shadow prices. This causes a beneficial "spiral up" in booking limits.

Combining the DAVN and ProBP results with the results from various network and leg RM combinations presented in Section 4.3, we conclude that revenue gains may be attained by airlines in alliances even when some partners use less sophisticated RM methods, and less frequent optimization. As long as both airlines participate in the code share itinerary availability decision by using BPS with dual control, or if code share itineraries have high network value (relative to local and connecting itineraries) and the partners use DV, then revenue gains can be obtained for the alliance from sharing bid or shadow prices from relatively infrequent optimizations.

Chapter 5

Results in Network E

This chapter provides a thorough analysis of the results for alliance network E, which was introduced in Chapter 3. The first part of the chapter provides a similar analysis to that of Chapter 4, demonstrating the benefits for network RM, BPS and DV, of more frequent optimization that produces more current bid prices, shadow prices, and booking limits. The chapter then proceeds to analyze the performance of BPS and DV for alliances 1 and 2 (comprising airlines 1 and 3, and 2 and 4, respectively) in network E at two demand levels, corresponding to the network load factors of 83% and 86% in the network RM scenarios without BPS or DV.

The organization of the chapter is as follows. The results when alliance 1 uses network RM (then applying BPS or DV), and the competitor, alliance 2, uses EMSRb, are presented first. The analysis first focuses on the benefits of daily optimization for BPS or DV, which prove to be acute in network E. Then, the results obtained when the competitor also uses the same type of network RM as alliance 1, but is not yet using BPS or DV, are shown. We then present the results for the competitive scenarios when alliance 2 rather than alliance 1 uses network RM, and applies BPS or DV. Finally, the results when both alliances use symmetric network RM and BPS or DV are presented.

Tables 5.1 and 5.2 provide summaries of the important characteristics of the four airlines in alliance network E in the baseline case for the medium and high demand levels, respectively, including load factors, revenues, and traffic details. Note that all four airlines use EMSRb in the network E baseline case, which was not the same in alliance network A4, where the 2 competitor airlines, 1 and 3, used DAVN and AT90, respectively. The percent revenue gains from network RM over the network E baseline (where all airlines use EMSRb) are larger in network E than in network A4 at similar load factors.

Code share traffic percentages (the last column) include both own and partner code share passengers for each alliance airline, because code share passengers occupy seats on both airlines' flight legs.

Airline	% Load Factor	*Revenue (000s)*	% Local	% Connecting	% Code Share	*Passengers Carried*	% Local	% Connecting	% Code Share
1-EMSR	82.6	1625	43	31	26	5911	51	29	20
2-EMSR	83.0	1820	48	30	22	6390	55	27	18
3-EMSR	83.2	1610	39	36	25	6182	51	30	19
4-EMSR	82.5	1652	43	32	25	5679	48	31	21

Table 5.1: Medium Demand Baseline Characteristics of Network E by Airline

Airline	% Load Factor	*Revenue (000s)*	% Local	% Connecting	% Code Share	*Passengers Carried*	% Local	% Connecting	% Code Share
1-EMSR	88.0	1743	43	31	26	6289	51	29	20
2-EMSR	88.4	1953	48	30	22	6814	55	27	18
3-EMSR	89.1	1729	39	36	25	6600	51	30	19
4-EMSR	88.4	1772	43	33	25	6084	48	31	21

Table 5.2: High Demand Baseline Characteristics of Network E by Airline

Tables 5.3 and 5.4 provide breakdowns, at medium and high demand levels, respectively, of the percentages of revenue and traffic generated by the three components, local, connecting, and code share, for the alliance as a whole. In network E, average code share fares are much lower, in relative terms, than they were in network A4. Average code share fares are only two to three times the local and connecting average fares. Compared to network A4, a similar percentage of revenues are provided by code share passengers, connecting passengers represent a smaller proportion of revenues, and locals a larger proportion. However, a substantially larger proportion of code share passengers are carried than in network A4.

The relatively lower average code share fares for both alliances in network E are the result of the fact that code share flights comprise a long-haul, trans-Atlantic flight leg, and at least one short haul leg. However, own connecting flights of any airline in one of the two alliances in network E may also comprise a long-haul and a short-haul leg (own connecting itineraries may also comprise two short-haul legs, which results in an overall lower average connecting fare). Whereas in network A4, the code share flights could include up to two long-haul legs, and own connecting itineraries could not, thus resulting in relatively higher average fares for code shares as compared to own connecting itineraries. Also, in network E, alliance 2 also has a lower average code share fare than alliance 1, and a substantially higher average local fare. Locals are the largest revenue source for alliance 2, and alliance 1 relies more on connecting and code share passengers for its revenues.

Component	Alliance	% Bookings	% Revenue	Average Fare
Local	1	57	41	215
	2	57	*46*	255
Connecting	1	33	34	305
	2	32	*31*	307
Code Share	1	11	26	704
	2	11	*23*	695

Table 5.3: Medium Demand Baseline Combined Alliance Revenue and Traffic Components

Component	Alliance	% Bookings	% Revenue	Average Fare
Local	1	56	41	217
	2	57	46	256
Connecting	1	33	34	307
	2	32	31	309
Code Share	1	11	26	707
	2	11	23	694

Table 5.4: High Demand Baseline Combined Alliance Revenue and Traffic Components

Now that we have introduced the chapter and presented some key aspects of network E, we proceed to the results in ProBP, followed by DAVN, for the cases described earlier.

5.1 Frequency of Optimization in Network RM, BPS and DV

This section, like Chapter 4 did for network A4, demonstrates the benefits of daily optimization over optimization at the start of 16 time frames for the network RM methods of ProBP and DAVN, and the additional benefits of applying the alliance RM techniques of BPS and DV.

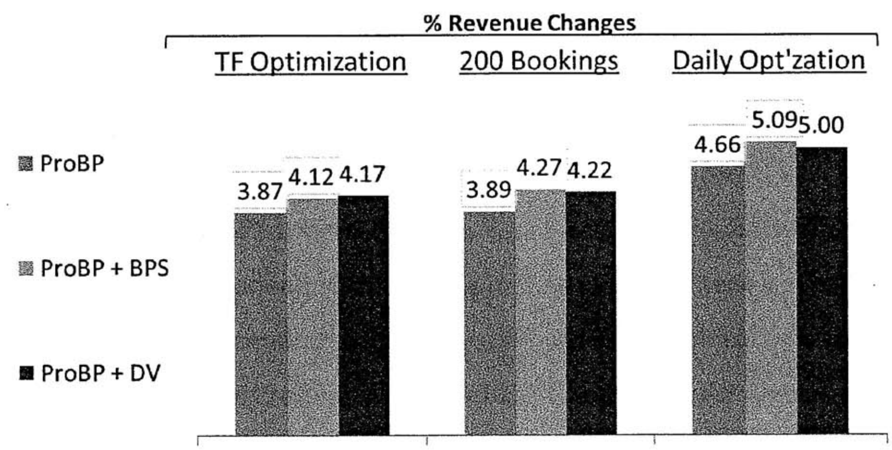

Figure 5-1: ProBP: Alliance Percent Change in Revenues over Baseline

Figure 5-1 shows that ProBP with daily optimization (calculation of prorated bid prices for all the legs in the network) gains +.79% over TF optimization, for the high demand scenario with an average network load factor of 86%. With daily optimization, BPS performs better than DV by about +.05%, but BPS does not outperform DV when optimization is at each time frame, in which case DV performs +.05% better than BPS. Note that network E (at 86% LF) carries fewer total passengers than A4 (83% LF), so optimization every 200 bookings occurs less frequently (closer to TFs) than in network A4, thus providing gains only slightly larger than TF optimization.

Looking at Figure 5-2, we see that as in network A4, daily optimization creates revenue gains in all traffic components by similar amounts for no BPS, BPS and DV. Gains are highest in the connecting traffic component (about +20 thousand), and second highest in the code share components (about +7-9 thousand), as in network A4. Also, switching from TF to daily optimization, when using BPS, produces larger revenue increases in the code share component than the increases when using DV.

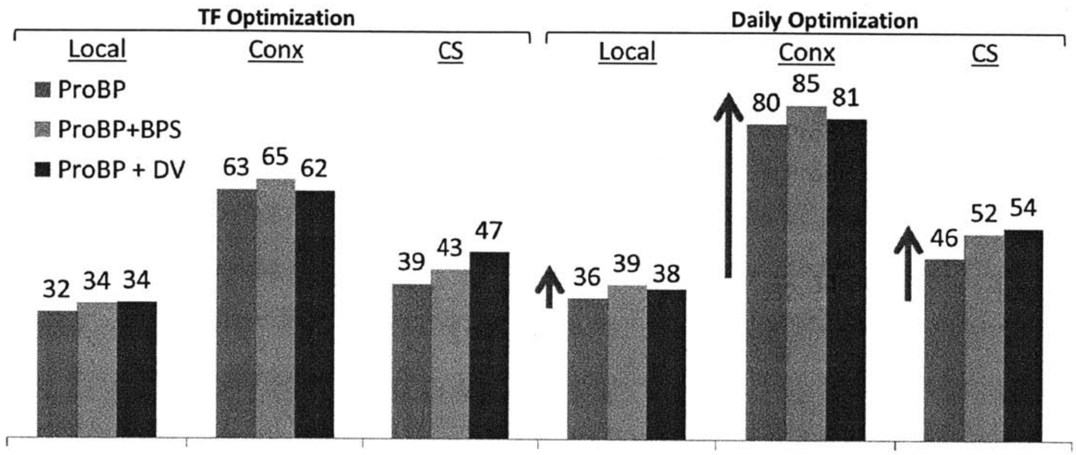

Figure 5-2: Change in Local, Connecting, and Code Share Revenues (000s) Compared to EMSRb Baseline

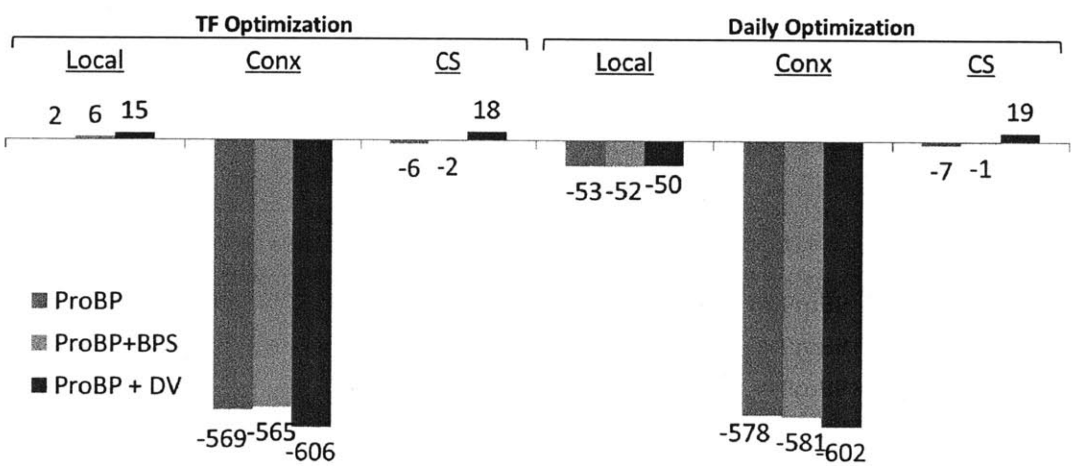

Figure 5-3: Change in Local, Connecting, and Code Share Traffic Compared to EMSRb Baseline

Figure 5-3 presents the changes in traffic in the three components. Daily optimization takes fewer locals, but other changes are not as prominent. Despite the decline in local passengers, the revenues increase in this component, indicating that the bid prices more accurately reflect the value of empty seats, and that they result in booking acceptance decisions that carry more high fare passengers than is the case for TF optimization.

The total code share passengers carried remains largely unchanged. The only other notable change is that, for BPS, applying daily optimization results in a larger reduction of connecting passengers. At both optimization frequencies, DV carries notably fewer connecting passengers and more code shares than either BPS or network RM without BPS, indicating that DV creates a preference for code share passengers over connecting passengers on routes that carry a large proportion of code share passengers. Also, though there are declines (or a very slight rise for DV) in connecting passengers with daily optimization, the revenue gains are large, indicating that the booking acceptance decisions are, as for locals, improving the fare class mix.

Change in Total Alliance Bookings

Opt'n	No BPS	BPS	DV
TF	-574	-562	-573
DAILY	-638	-635	-634

TF Optimization - Average Fares

Local	--------222--------		221
Conx	--------380--------		384
CS	--------742--------		↓734

Daily Optimization - Average Fares

Local	-----------224-----------		
Conx	386	388	390
CS	747	749	↓739

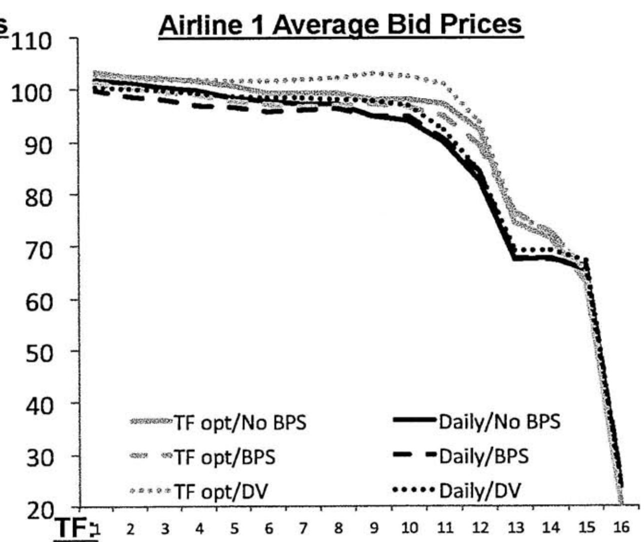

Figure 5-4: (Left) Change in Total Passengers from EMSRb Baseline, Component Average Fares. (Right) Average Bid Prices by Time Frame

Figure 5-4 shows the average bid prices for ProBP with no BPS, BPS, and DV in network E. We can see that, as in network A4, DV results in higher average bid prices than the other two methods, whereas BPS results in lower bid prices than standard ProBP with no BPS (particularly in the TF optimization case), thus allowing slightly more connecting and local bookings to occur in that case. On the other hand, the higher bid prices, due to DV, on routes with many code share passengers results in fewer connecting bookings in favor of code shares.

DV and BPS both cause increases in connecting fares, but DV produces large falls in code share fares (unlike in network A4). Recall that the average code share fare in network E is not as high, relative to local and connecting fares, as it was in network A4. This means that applying DV may not always raise the bid prices on routes with many code share passengers if the partner bid price is relatively high, but may in fact lower them, thus accepting too many low-fare code share bookings and lowering the average code share fare. BPS increases both average connecting and code share fares, but does not produce an increase in average bid prices because the valuation of code share itineraries remains the same as that of local itineraries.

5.1.1 DAVN for Alliance 1

Figure 5-5 shows that revenue gains are only +.12% from daily optimization above those from TF optimization, which is a very small improvement compared to the gain from DAVN in general, and smaller than the gain in network A4 even at a lower network load factor. Also, unlike in network A4, the performance of BPS and DV is severely affected by how up-to-date the bid prices are, with benefits only if optimization occurs daily.

When optimization occurs daily, BPS and DV produce large gains in connecting and code share revenues, as shown in Figure 5-6, but these gains do not occur with standard DAVN (without BPS or DV). The directional changes for switching from TF to daily optimization are indicated by red arrows, and the further changes from applying BPS and DV are indicated by black arrows. In the local component, there are moderate gains from daily optimization that are consistent for no BPS, BPS and DV.

When using standard DAVN, Figure 5-7 shows that local traffic increases from switching to daily optimization. Local traffic further increases, to a very large extent, from BPS and DV when optimization is at time frames, but the increase is significantly smaller with daily optimization. This indicates that the moderate increases in

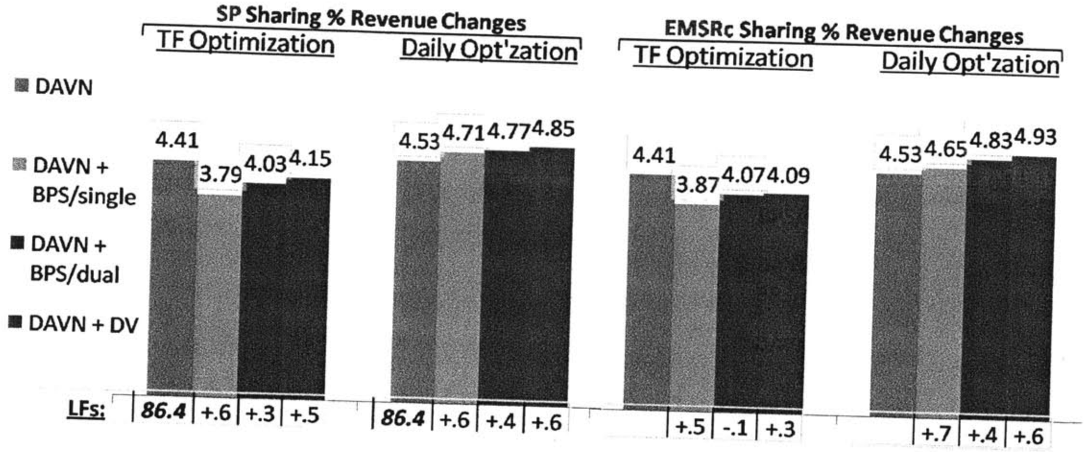

Figure 5-5: DAVN: Alliance Percent Change in Revenues over Baseline

revenues in the local component, due to BPS and DV when using TF optimization, come at the expense of carrying many more local passengers. These additional local passengers displace the connecting passengers, and cause large declines in connecting revenues. The same is not true in the daily optimization case, where BPS and DV cause a much smaller rise in local passengers, and a much smaller decline in connecting passengers. Thus, after applying BPS or DV, the modest revenue gains in the local component remain, but do not cause such declines in the connecting revenues.

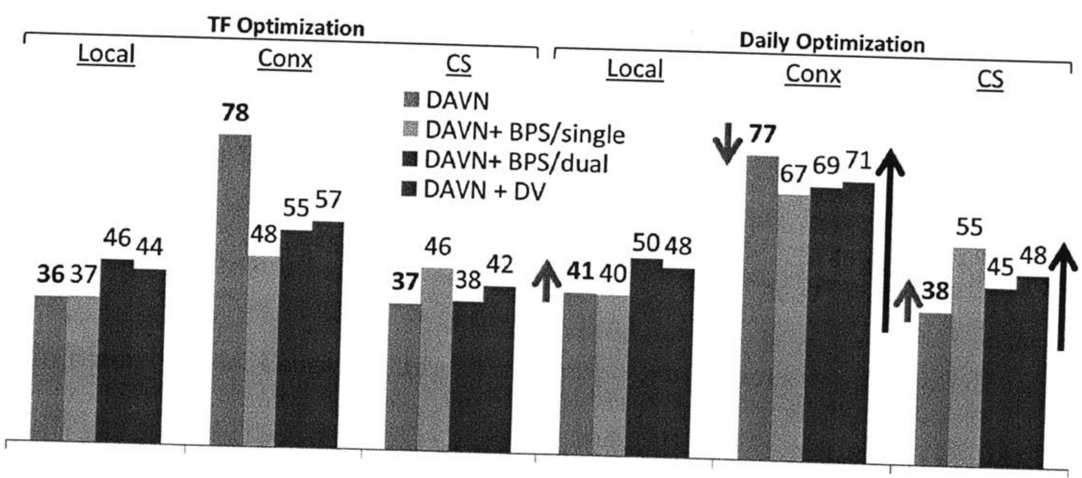

Figure 5-6: Change in Local, Connecting, and Code Share Revenues (000s) Compared to EMSRb Baseline

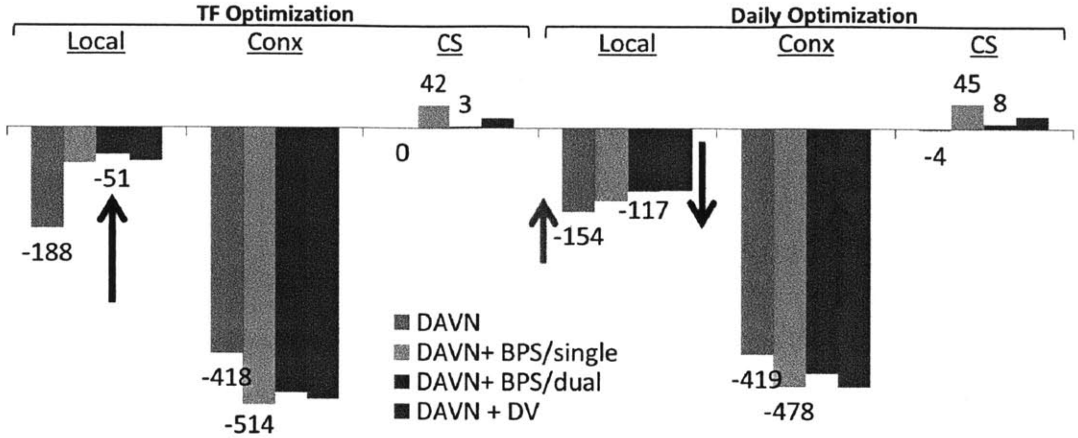

Figure 5-7: Change in Local, Connecting, and Code Share Traffic Compared to EMSRb Baseline

Change in Total Alliance Bookings

Opt'n	No BPS	BPS/ single	BPS/ dual	DV
TF	-606	-537	-539	-549
DAILY	-577	-568	-563	-572

TF Optimization - Average Fares				
Local	229	225	225	256
Conx	368	369	369	371
CS	737	720	735	730

Daily Optimization - Average Fares				
Local	---------------228---------------			
Conx	367	371	369	372
CS	740	725	738	732

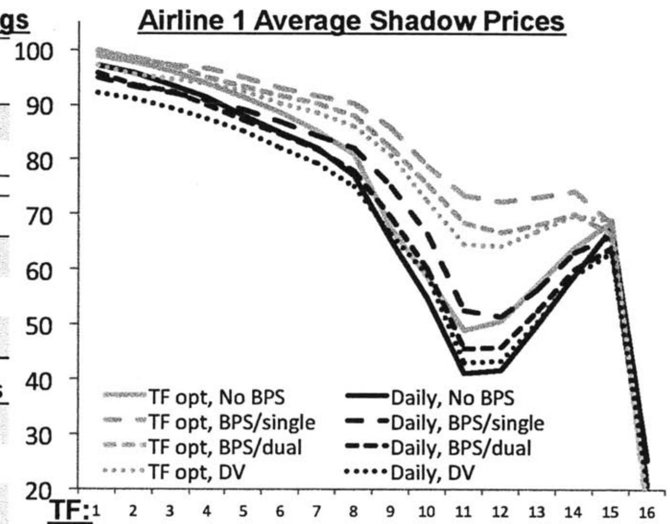

Figure 5-8: (Left) Change from EMSRb Baseline in Total Alliance Bookings, Component Average Fares. (Right) Average Bid Prices by Time Frame

BPS or DV produce increases in the number of code share passengers, and further applying daily optimization increases revenues more than the BPS/DV increase in the TF optimization case. These results are very different from those obtained in network A4, where the frequency of optimization had little impact on the success of

BPS and DV applied to standard DAVN.

Figure 5-8 shows the average shadow prices for the various scenarios. Shadow prices also fall with daily optimization, as in network A4. Also, like in network A4, all shadow prices start out at about the same level in the first time frames. However, a key difference is that BPS and DV cause very large rises in shadow prices in later TFs with TF optimization, whereas this is not so extreme for daily optimization. Shadow prices rise most from BPS with single control and least with DV (like the A4 DAVN case).

Although DV (with daily optimization) produces the best revenue gains, average shadow prices barely change from the values of no BPS with daily optimization, other than being slightly lower in early TFs, but slightly higher in later TFs. In comparison, shadow prices increase in all BPS scenarios.

5.1.2 Summary

As in network A4, ProBP gains significantly from optimizing daily (+.79%) due to more current bid prices. Revenue gains occur in all components, primarily in connections, and a fall in local traffic also occurs. Code share average fares increase due to BPS only with daily optimization, but they actually decrease with DV regardless of optimization frequency. This is because the average code share fares in network E are not as high relative to local and connecting fares, and DV can result in lower bid prices on some routes with heavy code share traffic, accepting more low fare code share passengers than without DV. For ProBP, there are always gains from BPS and DV (.25-.43% at 86% LF), increasing somewhat with more frequent optimization.

DAVN benefits only marginally from daily optimization (+.12), mainly in local revenues, due to a local traffic increase and higher average code share fares. However, BPS and DV only produce gains under daily optimization, when shadow prices are much more current, average connecting fares increase, and low fare local passengers do not displace connecting passengers as they do with TF optimization and BPS or DV. Code share fares never increase above those with standard DAVN, but BPS with dual control results in the highest code share fares of BPS and DV.

5.2 Alliance 1: BPS and DV at Different Demand Levels

In this section, we move to daily optimization in all cases, and focus on the benefits of BPS and DV for alliance 1 at two demand levels, 83% and 86% network load factors (LFs). We will examine how the modified alliance network E benefits from daily BPS or DV when used by alliance 1.

5.2.1 Alliance 1 uses ProBP

The following subsection describes the results obtained when alliance 1 uses ProBP, then applying BPS and DV. The subsection is divides into two parts, where the competitor, alliance 2, uses EMSRb or ProBP (without BPS or DV).

Competitor Alliance 2 uses Leg RM

Figure 5-9 shows that BPS and DV, when applied to ProBP with daily optimization used by alliance 1, both cause important percent revenue gains for alliance 1 over the EMSRb baseline, in the case when the competitor uses EMSRb. DV produces larger revenue gains than BPS at medium demand, and the effect is reversed at high demand. The LFs for the alliance increase due to BPS and DV as a result of more long-haul itineraries being booked. At high demand, DV causes a larger increase in the LFs of the alliance than BPS because it increases the sales of long haul code share itineraries even more than BPS, but this does not cause as much of a revenue gain.

Figure 5-10, showing the changes from baseline in revenue (thousands) and traffic at high demand in the same chart, illustrates that alliance 1 revenue gains come from code share revenues and traffic, with larger gains in both from DV than BPS. DV causes the largest falls in connecting traffic and takes the most local and code shares bookings. BPS produces better total revenue gains than DV by gaining the most revenue in connections and locals, and making better code share decisions (i.e., taking fewer code share and local bookings than DV).

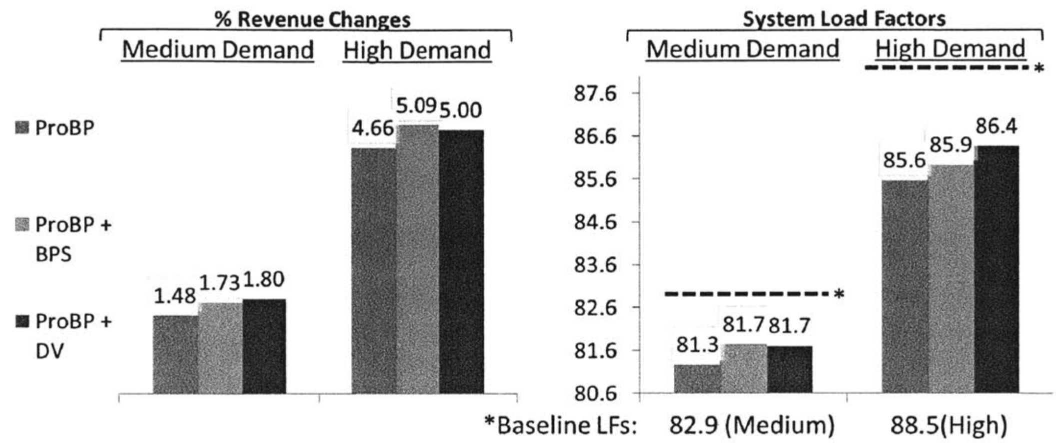

Figure 5-9: Alliance Percent Change in Revenues over EMSRb Baseline (Alliance 2 uses EMSRb)

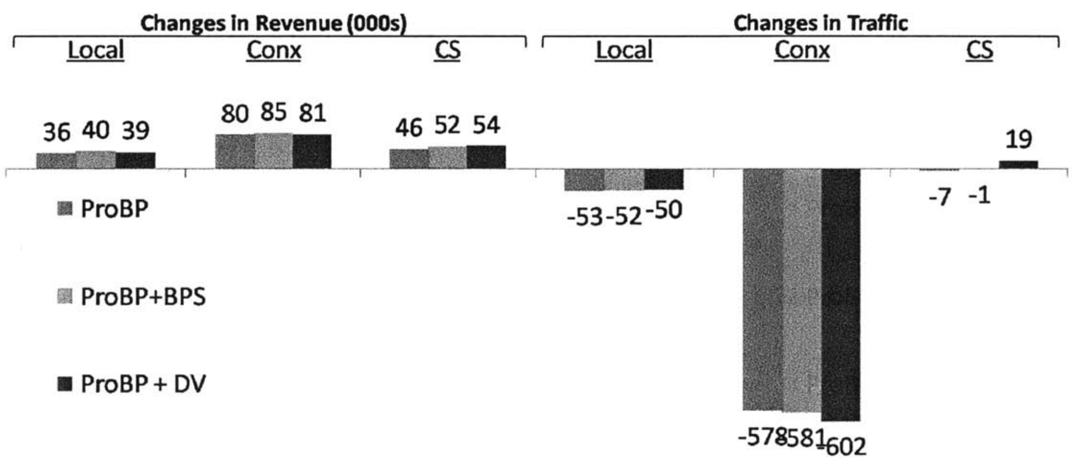

Figure 5-10: Change in Local, Connecting, and Code Share Traffic and Revenues (000s) Compared to EMSRb Baseline

Competitor Alliance 2 also uses Network RM

Figure 5-11 shows that gains from network RM with daily optimization are halved when both alliances use ProBP. This occurs because the revenue gains from network RM methods, which occur from the RM system generating improved booking availability decisions that better account for the network value of local and connecting itineraries, are now divided between the two alliances.

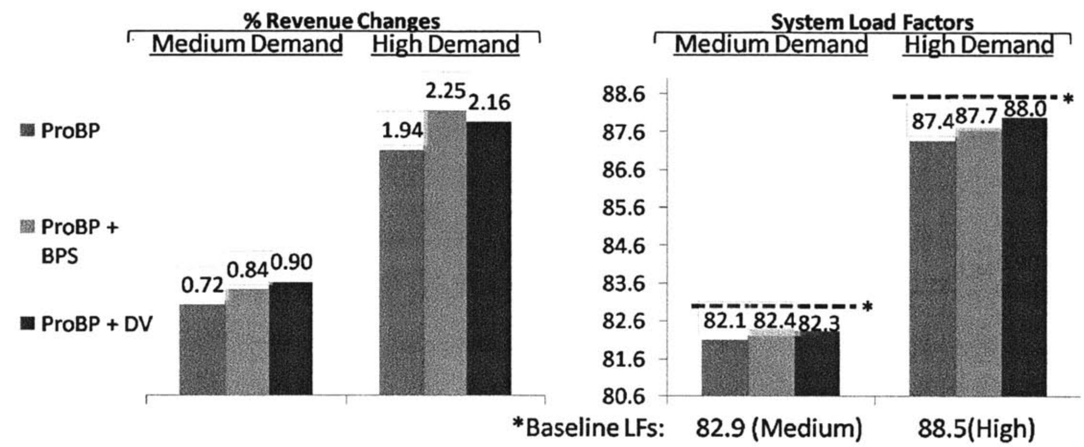

Figure 5-11: ProBP: Alliance Percent Change in Revenues over EMSRb Baseline (Alliance 2 uses ProBP)

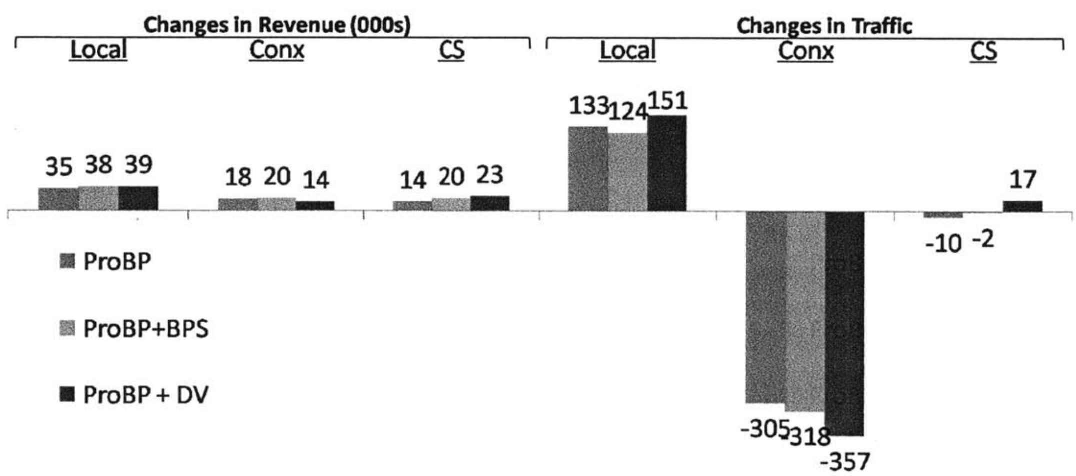

Figure 5-12: High Demand: Change in Local, Connecting, and Code Share Traffic and Revenues (000s) Compared to EMSRb Baseline

Just like in the prior case when the competitor used leg RM, BPS outperforms DV at high demand, whereas DV performs best at medium demand. At high demand, the stricter control of code share itineraries with BPS prevents code shares from occupying the seats of high-revenue own local and connecting passengers. Whereas, in the medium demand scenario, DV performs better by accepting more code share passengers, which do not displace high-revenue own local and connecting passengers when demand is relatively low and there are more remaining seats.

We can see in Figure 5-12 that, unlike the prior case, network versus leg RM, now more local passengers are carried, and the largest revenue and traffic gains come from that component (no longer from connections). More so for DV, but also for BPS, revenue gains come from code share (and local) revenues and traffic. Large falls in connecting traffic do not have a large effect on connecting revenues, indicating that both methods improve the fare class mix of connecting traffic.

5.2.2 Alliance 1 uses DAVN

The following subsection describes the results obtained when alliance 1 uses DAVN with daily optimization, and the two alliance airlines both exchange shadow prices or EMSRc values when applying BPS and DV. The subsection is divided into two parts, like the previous ProBP discussion, where the competitor uses EMSRb or ProBP (without BPS or DV).

Competitor Alliance 2 uses Leg RM

We can see from Figure 5-13 that BPS only produces gains at high demand, and the gains are similar for EMSRc and SP exchange. The gains are higher for dual control (.24 to .30%) than for single control, exactly as we have seen before. However, at low demand, both SP and EMSRc exchange actually produce small revenue declines of about -.03% from standard DAVN. On the other hand, DV produces gains at both demand levels, but the gains are marginal at medium demand (.04%) and increase to as much at .40% at high demand.

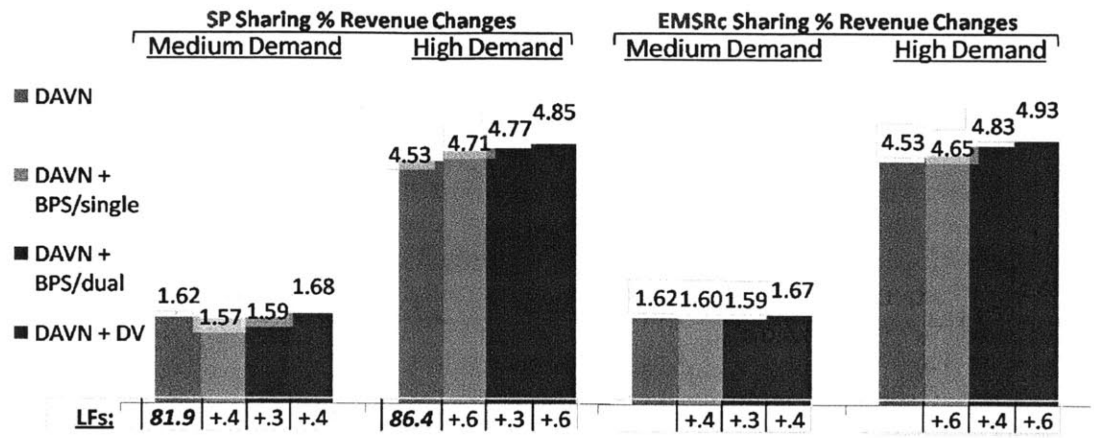

Figure 5-13: DAVN (SP or EMSRc Exchange): Alliance Percent Change in Revenues over EMSRb Baseline (Alliance 2 uses EMSRb)

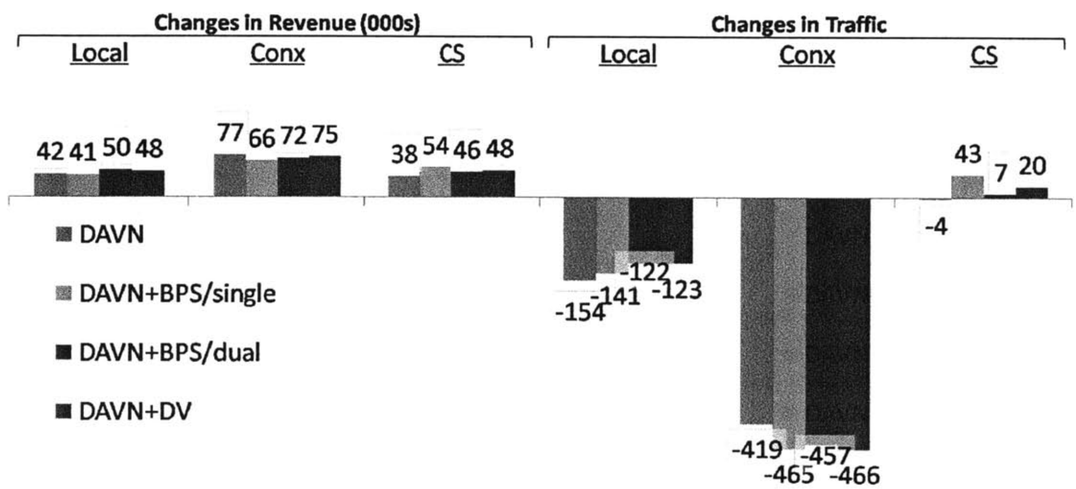

Figure 5-14: Change in Local, Connecting, and Code Share Traffic and Revenues (000s) Compared to EMSRb Baseline (DAVN SP Exchange)

Figure 5-14 shows the breakdown of component traffic and revenues (in thousands) for the high demand scenario when the alliance partners exchange shadow prices. Although DV does not produce the largest gains in any single component, it loses less than BPS in connecting revenues while gaining substantially in locals and code shares.

The large fall in connecting traffic combined with a small decrease in connecting revenues indicated that the connecting traffic fare class mix is improved, and the decline in passengers creates room for an increase in local and code share bookings.

Competitor Alliance 2 also uses Network RM

In the case where the other alliance also uses network RM, just as we have seen in the prior section, DV consistently performs better than BPS for alliance 1, raising revenues by +.11-.15% for both medium and high demand levels. Also, BPS with dual control performs almost as well as DV, and better than BPS with single control, which gains slightly even at high demand (+.01-.06%). As before, the exchange of shadow prices of EMSRc values does not produce important differences in the results.

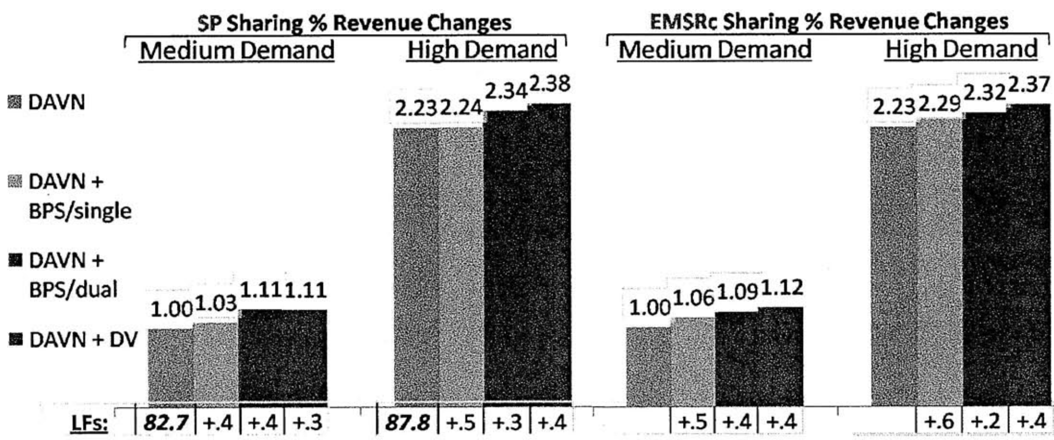

Figure 5-15: DAVN (SP and EMSRc Exchange): Alliance Percent Change in Revenues over EMSRb Baseline (Alliance 2 uses DAVN)

Unlike in the case where the competitor uses leg RM, BPS produces gains even at medium demand. The more sophisticated RM of the competitor creates a positive feedback effect that reflects well on alliance 1 as well. When the competitor is also using a more sophisticated RM method such as DAVN, then low fare classes on certain itineraries are may not be available on any alliance airline. As a result, passengers will be more likely to buy the next highest available fare on either alliance, resulting in benefits to both alliances that may not have been present in the scenario where the competitor used a leg-based RM method such as EMSRb.

5.2.3 Summary

For alliance 1, DV with daily optimization generally leads to the highest revenue gains for both DAVN and ProBP under medium demand, however, ProBP with BPS performs better than DV at high demand. When the competitor also uses ProBP, the pattern of gains over standard ProBP is similar, but smaller.

With DAVN for alliance 1 and EMSRb for the competitor, BPS does not improve revenues at the medium demand level because code share gains do not make up for losses in connecting (and local) revenues (the component revenue breakdown was not shown for medium demand). DV gains +.06% through better local and good code share revenues, but still loses connecting revenues. At high demand, gains occur from both BPS and DV. When the competitor uses DAVN as well, the order of gains from BPS and DV remains the same, but all methods produce revenue gains at both medium and high demand levels because of a beneficial competitive feedback effect.

5.3 Alliance 2 uses BPS or DV while Alliance 1 Does Not

This section shows the results obtained when alliance 2 (which has different characteristics than its competitor), rather than alliance 1, uses BPS and DV. We show the results for the medium and high demand scenarios, as before, where network load factors are about 83% and 86%, respectively. We discuss the results from two scenarios: alliance 2 using network RM, and competitor alliance 1 using leg RM (EMSRb), and the competitor also using the same network RM (ProBP or DAVN). All results involving network RM use daily optimization, and all changes shown are relative to the baseline case where all four airlines use EMSRb.

5.3.1 Alliance 2 uses ProBP

Figure 5-16 illustrates that BPS generally produces the largest revenue gains for alliance 2 at each demand level, and in each competitive case, regardless of whether the competitor uses EMSRb or DAVN. At medium demand, the revenue gains due to BPS are relatively small, at about +.08%, in both the case where the competitor uses EMSRb and also the case where the competitor uses ProBP. The benefits of BPS increase further at high demand, to as much as .38%, whether the competitor uses leg or network RM. However, relatively small gains from DV remain, though not as large as they were for alliance 1, indicating that alliance 2 does not benefit as much from DV as did alliance 1.

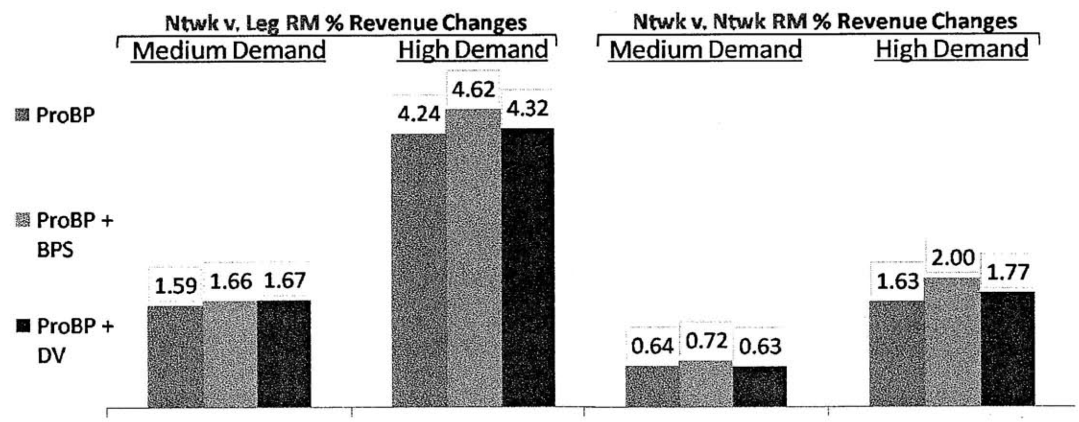

Figure 5-16: Alliance Percent Change in Revenues over EMSRb Baseline (Left: Competitor uses EMSRb, Right: Competitor uses ProBP)

Figure 5-17 shows that at higher LF, the gains from BPS are due to large rises in connecting bookings revenue. However, code share revenues actually decline from both BPS and DV. Although the small code share revenue decline from BPS paired with the large fall in code share passengers indicates an improved fare class mix, the same is not true for DV. DV takes just as many code share passengers but produces a fall in code share revenues, a smaller increase in connecting revenues, and a fall in local revenues as well. For BPS, taking fewer code share passengers leaves more room for connecting bookings, and results in more revenues.

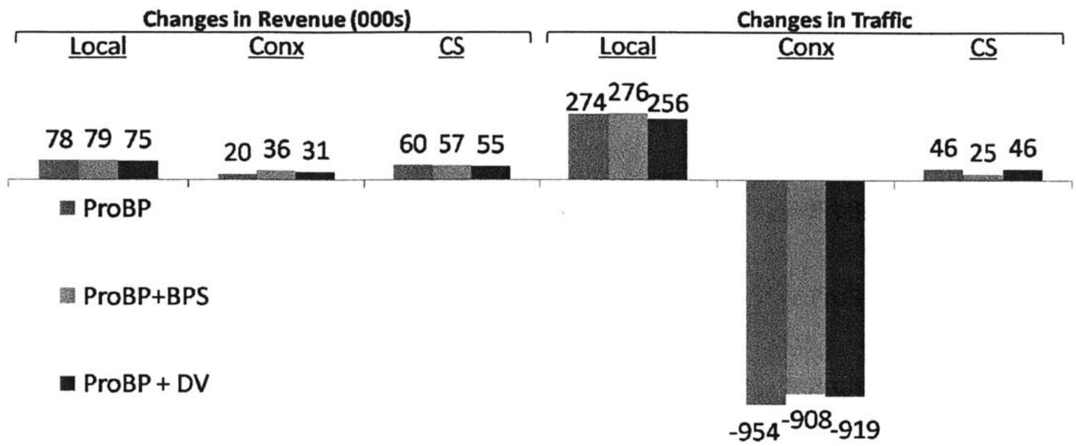

Figure 5-17: High Demand: Change in Local, Connecting, and Code Share Traffic and Revenues (000s) Compared to EMSRb Baseline (Alliance 1 uses EMSRb)

5.3.2 Alliance 2 uses DAVN

When alliance 2 uses DAVN with daily optimization and applies BPS or DV, the only benefits occur from BPS with dual control at high demand, as seen in Figure 5-18. Although a tiny gain of +.02% occurs with DV at high demand when the competitor uses EMSRb, this does not hold true when the competitor uses DAVN. At medium demand, all of the methods cause losses.

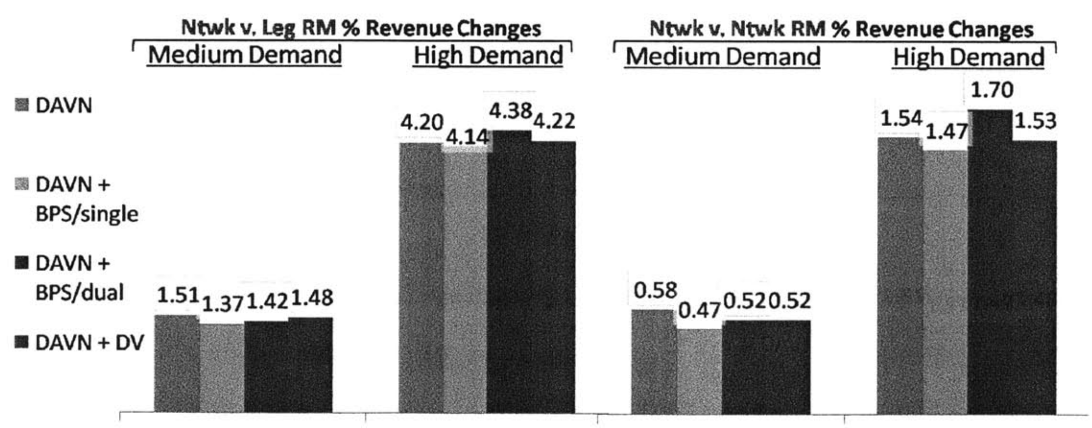

Figure 5-18: Alliance Percent Change in Revenues over EMSRb Baseline with DAVN SP Exchange (Left: Competitor uses EMSRb, Right: Competitor uses DAVN)

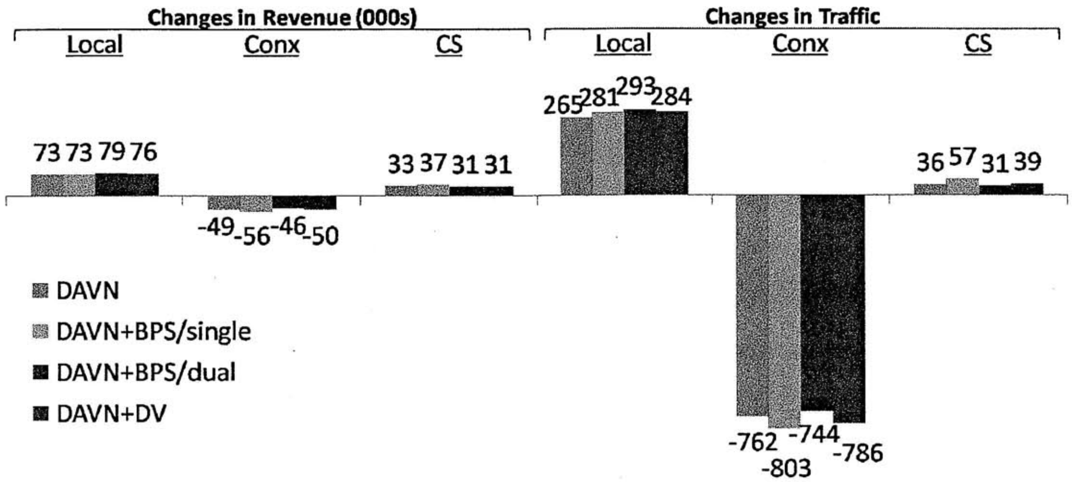

Figure 5-19: High Demand: Change in Local, Connecting, and Code Share Traffic and Revenues (000s) (Competitor uses EMSRb, Alliance 2 uses DAVN with SP Exchange)

Figure 5-19 shows the changes in revenue and traffic components for alliance 2. When alliance 2 uses BPS and single control or DV, there occur minor gains in code share revenues from carrying more code share passengers, but the minor gains do not make up for losses in connecting bookings and revenues.

However, BPS with dual control performs well by actually taking the least code share passengers while but losing little code share revenue, indicating an improved fare class mix. This also leaves some room for local and connecting bookings, thus gaining revenues in those segments. These observations are very similar for EMSRc exchange (for which the component breakdown is not shown).

5.4 Both Alliances use BPS or DV

This section shows the results obtained when both alliances start out using network RM, and then both apply BPS or DV. We show the results for a high demand scenario, where network load factors are about 86%. We first present the results for ProBP and then for DAVN, in each case with daily optimization.

5.4.1 Both Alliances use ProBP

Figure 5-20 shows that BPS and DV both help alliance 1 marginally, with DV providing only slightly higher revenue gains. However, for alliance 2, BPS results in even more minor gains of only .02%, and DV causes large losses of -.28%. These losses are accompanied by falls in the LF for alliance 2, whereas alliance 1 increases its LFs slightly. These results indicate that only BPS with dual control consistently helps both alliances.

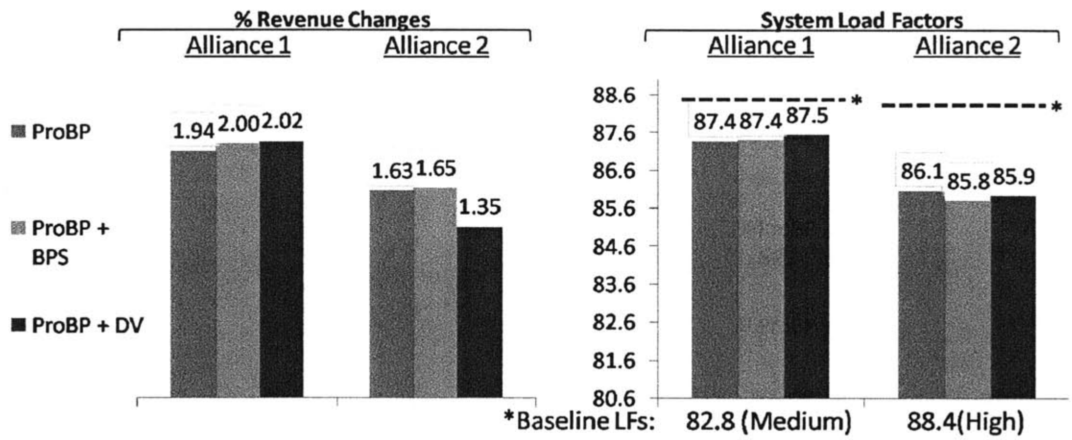

Figure 5-20: Both Alliances use ProBP: Percent Change in Revenues over EMSRb Baseline

Figure 5-21 shows the revenue component changes from baseline for each alliance, and Figure 5-22 shows the traffic component changes. We can see that the lower LFs for alliance 2 are due to fewer code share passengers carried using network RM, and further LF falls are due to declines in code share passengers. The minor gains of BPS come from gains in connecting and local revenues that barely offset the falls in local revenue.

Alliance 1 gains code share and local revenues with both BPS and DV, making up for losses in connecting revenues. These gains come from improved fare class mix in local traffic. The ratio of traffic to revenues indicates that BPS produces a better fare class mix in code share traffic than DV, but DV a better mix in connecting traffic.

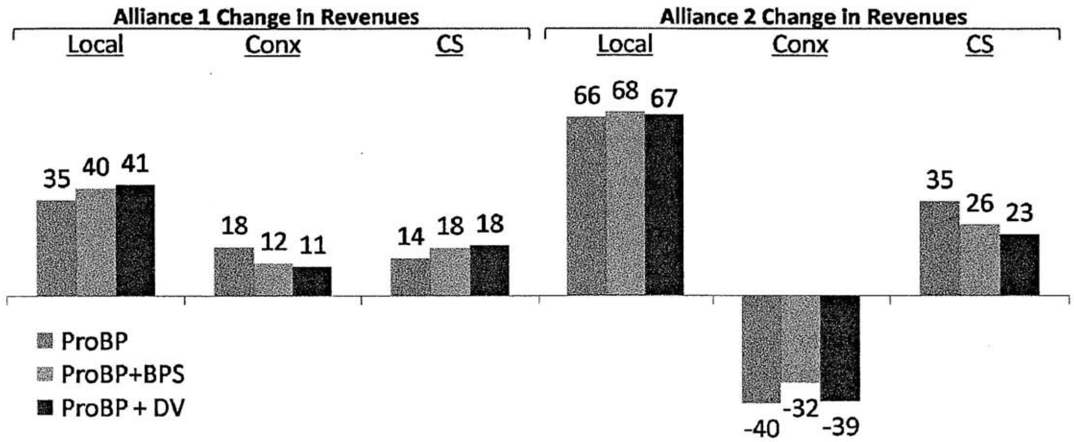

Figure 5-21: Change from EMSRb Baseline in Local, Connecting, and Code Share Revenues (000s)

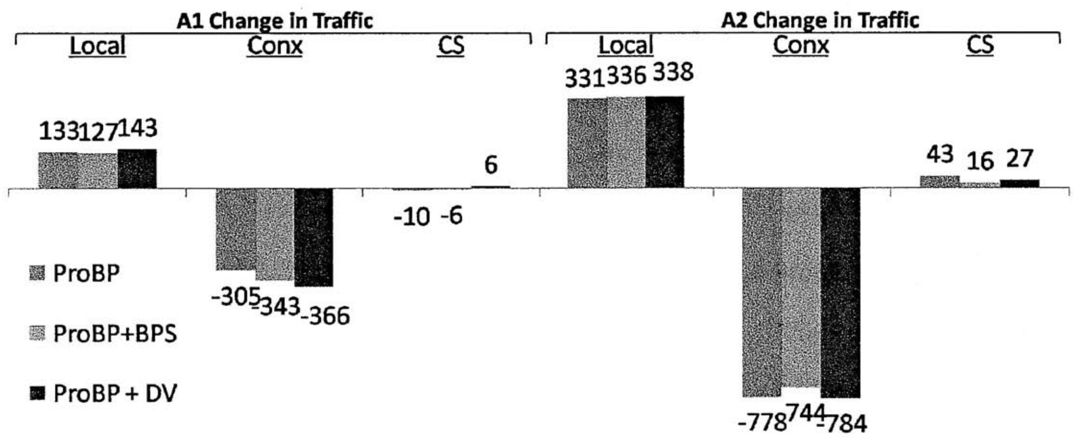

Figure 5-22: Change in Local, Connecting, and Code Share Traffic

Figure 5-22 shows that for alliance 2, code share traffic declines, more from BPS than DV, having increased a lot from ProBP alone. It is clear that the structural differences between the two alliances produce different changes due to the application of network RM. DV only helps alliance 1, but harms alliance 2, because of underlying structural differences between the alliances, in terms of the proportion of revenues and traffic, and the average fares, in the local, connecting, and code share components.

For example, the larger decline in load factors for alliance 2 than alliance 1 following the application of ProBP, and then BPS or DV, is because alliance 2 experiences a fall in the length of trips taken on its network. Local passengers, with their relatively high average fares, are given preference over connecting passengers (as can be seen in Figure 5-22, but this is not true to the same extent as for alliance 1. In addition, BPS for alliance 2 results in a decline in code share bookings, and an increase in local passengers, whereas the opposite occurs for alliance 1.

5.4.2 Both Alliances use DAVN

Figure 5-23 indicates that DAVN produces much larger gains for alliance 1 than it does for alliance 2. Though this was also true for ProBP, the gap was not nearly as large. Secondly, it is clear that the results for DAVN are consistent with the ProBP case. Alliance 1 benefits marginally from BPS (more so from BPS with dual control, as expected), and more from DV. In fact, the benefits from DV are more substantial (+.12%) in the DAVN case than in the ProBP case.

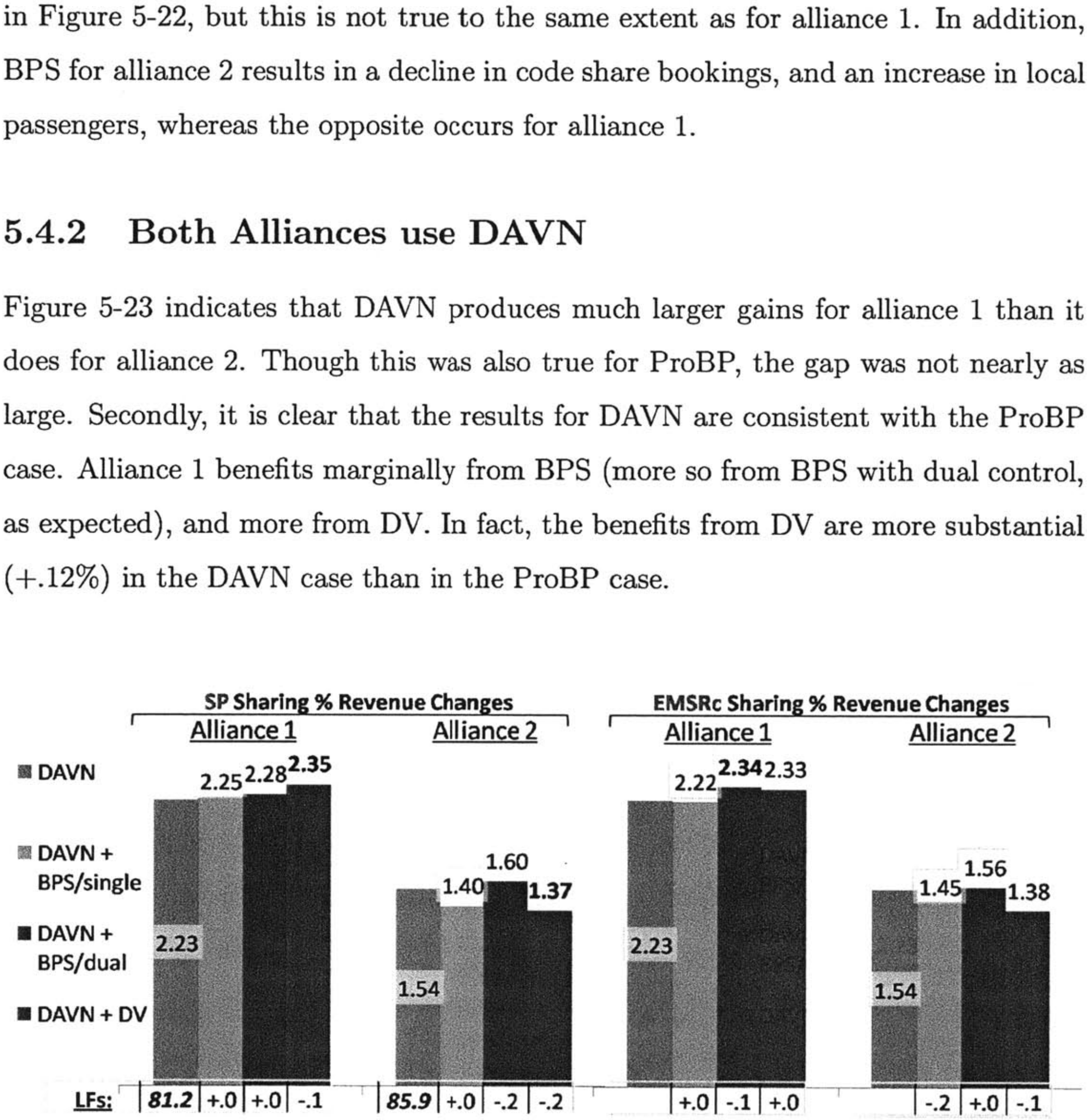

Figure 5-23: Both Alliances use DAVN (SP or EMSRc Exchange): Percent Change in Revenues over EMSRb Baseline

The same is not true for alliance 2, which experiences small revenue gains (+.06%) only from BPS with dual control, in fact gaining more than in the ProBP case. DV and BPS with single control both cause losses for alliance 2, with the largest losses from DV, like in the ProBP case. The results are similar whether SPs or EMSRc values are exchanged.

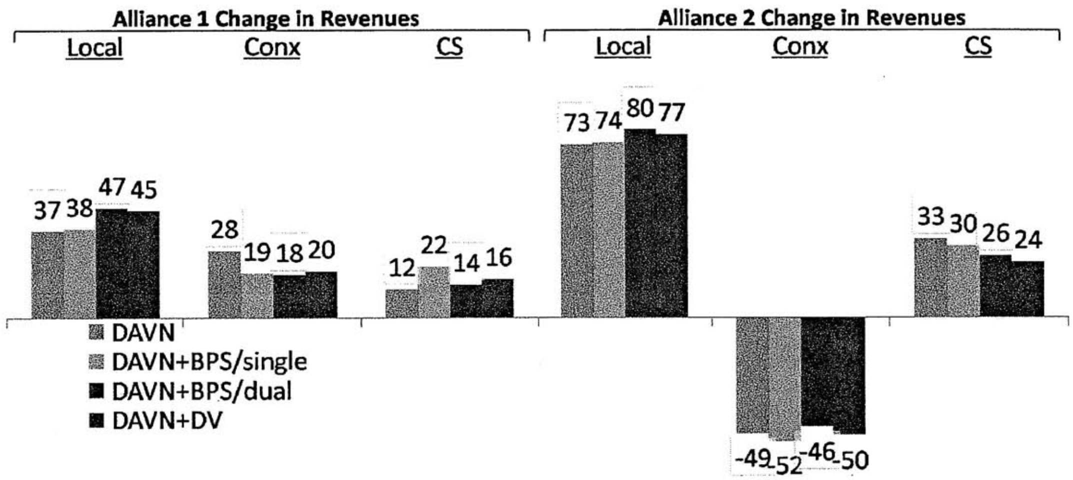

Figure 5-24: Change in Local, Connecting, and Code Share Revenues (000s), DAVN SP Exchange

The difference in the performance of the two alliances are due to their inherent structural differences causing different reactions to network RM, BPS, and DV. Looking at Figure 5-24, alliance 1 gains code share revenues when using BPS or DV, having started out with a smaller revenue gain in code shares from standard DAVN. In addition, the remaining revenue gains come from gains in the local component, while there are losses in connecting revenues from BPS and DV.

Alliance 2 actually loses code share revenues from all methods. It also gains local revenues from all methods, and the largest local revenue increases are with BPS and dual control, just as for alliance 1. However, the reason why BPS with dual control is the only method that produces an overall revenue increase for alliance 2 because only it produces improved connecting revenues as well. BPS with single control and DV cause losses in that component.

5.4.3 Discussion of Differences between Alliances 1 and 2

We have seen that BPS with dual control is the only method that consistently helps both alliances. BPS with dual control works best for alliance 2 in all cases, while DV works best for alliance 1. The reason that DV works better for alliance 1, and not as well for alliance 2 (sometimes not working at all), is because of differing network parameters. Recall that alliance 1 obtains a larger percentage of revenues from code share and a smaller proportion from local itineraries. Alliance 2, on the other hand, obtains less revenue from code share and more from local itineraries. In addition, alliance 2 has a lower average code share fare than alliance 1, and a much higher average local fare.

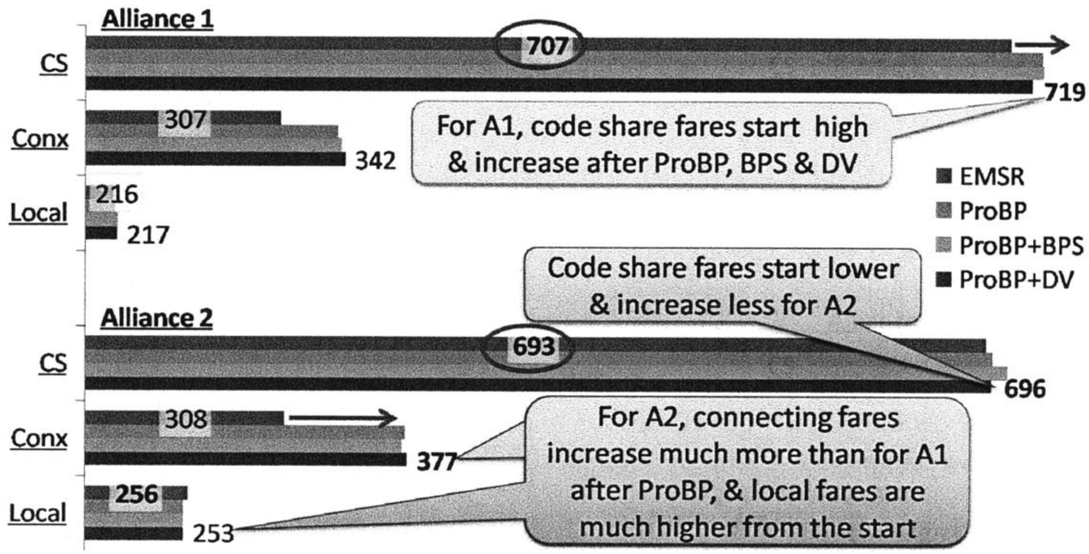

Figure 5-25: Alliance 1 and Alliance 2 ProBP Average Local, Connecting, and Code Share Fares

Figure 5-25 illustrates the average component fares for alliances 1 and 2, and shows how the average fares change after the application of ProBP, and additionally BPS and DV. Code share fares increase more for alliance 1 than for alliance 2 when applying network RM and further alliance RM techniques. Connecting fares also increase much more for alliance 2 than alliance 1, making that component more important for revenues. When DV is used by alliance 2, subtracting the already higher bid prices (resulting from the higher local fares of alliance 2) from the lower code share fares causes spiral down and harms revenues. This does not occur for alliance 1 because of its inherently higher code share fares and lower local fares.

5.5 Chapter Conclusions

When using DAVN, the frequency of optimization is a key factor affecting the performance of BPS and DV in network E. When shadow prices are calculated every 7 days during the first portion of the booking process, and the partner uses these stale shadow prices for determining code share flight availability, the result is detrimental to revenues.

The DAVN heuristic results in many more low fare local bookings, which occupy the seats that are not being sold as parts of code share itineraries. With the high shadow prices in the TF optimization with BPS or DV scenario, the lack of code share bookings filling the seats on the short-haul domestic legs leaves them open for low-fare local passengers. The DAVN booking limits are also only recalculated 16 times, which does not allow the updating of booking limits on low-fare local itineraries at a rate that is fast enough to keep up with changes in the state of the system. The version of DAVN used in the PODS simulation only uses eight virtual buckets. Experiments with 16 virtual buckets produced smaller revenue declines, but did not correct the problem. Because this DAVN implementation may not represent the current or most sophisticated practices of some airlines, the results obtained here are not generalizable to all DAVN implementations.

The same is not true for ProBP. As observed in network A4, even exchanging dated bid prices for use in code share availability control via BPS or DV, calculated at the start of 16 time frames, results in revenue gains for the alliance above those of standard ProBP network RM. These revenues gains are higher, however, with daily optimization of bid prices, whereas the percent revenue gains from BPS or DV were the same in network A4 regardless of the frequency of optimization.

The revenue gains are still present for alliance 1 even when alliance 2 uses network

RM as its revenue management method rather than EMSRb. However, the resulting revenue gains are smaller when the competitor uses a more intelligent RM system.

Alliance 2 also benefits from BPS when the competitor uses EMSR, but less than the benefit for alliance 1. When the competition uses network RM, the revenue gains are smaller than they were for alliance 1 as well.

When both alliance use BPS or DV, alliance 1 retains a revenue gain from BPS and DV. The gain for alliance 2, in this situation, is very minor will BPS. DV, however, causes losses for alliance 2 when its competitor also uses DV. Recall that code share average fares are lower for alliance 2 than for alliance 1, and average local fares are higher. Also, locals comprise the largest proportion of revenues for alliance 2, and code shares a smaller proportion, as compared with alliance 1. The lower code share fares combined with the higher local fares results in a spiral down effect for alliance 2 when using dynamic valuation, whereas the competitor does not experience a revenue decline because of different network characteristics.

In network E, which differs from network A4 in terms of its physical structure, the properties of the types of flights (short-haul local and domestic connecting, along with long-haul international code share flights), the benefits of BPS and DV depend on the network characteristics and how current the bid prices are to a larger degree. If code share flights are high-revenue relative to local itineraries, then BPS and DV improve revenues by raising bid prices (ProBP) or improving booking limits (DAVN). These benefits are more pronounced, and do not affect the revenues from the other traffic components, when code share itineraries comprise a larger proportion of revenues.

If, however, the airlines in an alliance do not obtain the majority of revenues from code share traffic and the average code share fare is relatively low compared with the average local fare, then the potential danger of displacing a local passenger and causing revenue loss presents a problem for implementing BPS and DV.

The benefits from BPS and DV are present in most cases for alliances of differing structure, and they are larger if the competition is using less sophisticated RM methods. Additionally, if two competing alliances differ in their network characteristics such that one carries higher-revenue code share passengers and obtains a large amount of revenues from that component, then it could experience a larger benefit from BPS and DV to the detriment of the competitor.

The results indicate that the frequent optimization of bid prices and booking limits may be particularly important in networks with a large difference in the lengths of their sets of flight legs, intense competition between two alliances, and semi-restricted fare structures in some parts of their networks that are prone to spiral down.

Chapter 6

Conclusion

This thesis examined revenue management (RM) and seat availability control methods that airline alliance partners can adopt to improve the total revenues of the alliance without formally merging. Partners can share information about the network opportunity costs of selling seats on their flight legs, called "bid prices". The exchange of bid prices among alliance partners, termed bid price sharing (BPS), allows airlines participating in alliances to incorporate information about the estimated value of seats on their alliance partners' flight legs into their decisions about which code share itineraries to accept or reject. The timeliness of the bid price exchange and the frequency of calculation of bid prices throughout the booking process were also analyzed.

Cooperative alliance seat availability control methods involving BPS improve code share itinerary availability decisions because the presence of code share flights presents a problem for individual airline RM systems. Because partners do not jointly optimize revenues on code share flights, alliance revenue gains from implementing origin-destination (O-D) availability control (also called network RM) may be lower than an individual airline's gains.

In BPS code share availability control, the leg bid prices of the two alliance partners are compared against the total code share itinerary fare, and if the fare value exceeds the sum of the bid prices, then the code share itinerary is available for booking. Under single airline control, only the partner selling the itinerary (the marketing partner) checks that the fare exceeds the sum of the bid prices that it has on hand, but under dual control, both airlines check that the code share fare is higher than the bid price sum. Single and dual control will result in different code share acceptance decisions if the bid prices used by the partners in their evaluations differ. If so, then dual control will result in the acceptance of fewer code share bookings because the code share fare must exceed the larger of the two bid price sums.

Dynamic valuation (DV) is a method that modifies the perceived value associated with a code share itinerary, given as input to an airline's RM system, dynamically throughout the booking process. Rather than being valued the same as a local itinerary traversing the same flight legs that a code share itinerary does, DV values the code share itinerary at the total code share fare less the partner's bid price on its operated flight legs. The advantage of DV is that it incorporates recent information about the status of the operating partner's legs in the RM system of the marketing partner. The disadvantage is that modifying the valuation of code share flights in the RM system can be more difficult to implement than BPS seat availability control, and can also affect the availability of own local and connecting itineraries through altered bid prices and booking limits, because their modification affects the entire network.

6.1 Research Findings

A simulation-based research tool called the Passenger Origin-Destination Simulator (PODS) was used for the experiments in this thesis. Several RM techniques, which attempt to optimize airline revenues at the flight leg or network level, were tested in conjunction with BPS, in two alliance network environments. The US-based network A4 comprises four airlines, all with hubs in the central region of the US, with one alliance, and two other non-allied airlines. In network E, two competing airlines in the US and two in Europe make up two competing trans-Atlantic alliances. The average fares of code share itineraries, relative to those of own (non-code share) local and connecting itineraries, are much higher in network A4 than in E, but the proportion of code share revenues and passengers is higher in network E than in A4.

With regard to the frequency of the RM system's optimization, and thus the frequency of bid price calculation and exchange, it was found that optimizing daily, versus at the start of 16 time frames throughout the booking process, provides higher revenue gains for both ProBP and DAVN. The gains from more frequent optimization are higher for ProBP than for DAVN. ProBP is based on optimal proration of fares across the entire network, and depends on the accuracy of estimates of forecasted demand to remaining capacity for bid price calculation. Therefore, using the most recent booking data for the calculation of ProBP bid prices will produce bid prices that better reflect the current value of empty seats. For the heuristic DAVN, the more frequent optimization provided gains that were at most half as large as those of the ProBP case. However, DAVN, optimized at the start of each time frame, starts out providing larger revenue gains than ProBP.

Of the two simulation networks tested in this thesis, exchanging bid prices from more frequent optimizations was found to be much less critical to the success of BPS and DV in network A4 than in network E. In network A4 at 83% load factor, the additional gains from BPS with dual control and DV (+.03 to .06% and +.24 to .29%, respectively) above standard network RM were found to be very similar regardless of the frequency of optimization.

However, in network E, the optimization frequency was found to have an important effect on the success of BPS and DV, that was also different for the two network optimizers ProBP and DAVN. The following conclusions are for the results in network E when the competitor used EMSRb. With ProBP in network E, exchanging bid prices from optimizations that occurred at the start of 16 time frames produced further revenue gains of +.25 to +.30%, for BPS and DV, respectively, beyond standard network RM. The gains of exchanging bid prices from daily, as opposed to time frame, optimization were almost 50% higher (+.34 to .43%), with BPS performing better than DV at high optimization frequencies.

The results were different for DAVN, where bid price exchange from optimizations at each time frame caused revenue losses of -.62 to -.26%., which were worst for BPS with single control. On the other hand, daily optimization with BPS and DV produced large gains that reached +.40% when the alliance partners used DV and exchanged DAVN leg EMSRc values as bid prices.

Chapter 4 of this thesis served as a continuation of the work of Jain (2011) and presented the results related to BPS and DV in PODS alliance network A4. The implementation of DAVN with BPS was modified so that the EMSR virtual bucket booking limits used local code share valuation instead of the total code share fare less the partner's leg bid prices. Also, rather than requiring the code share fare to exceed the sum of own EMSRc value and partner bid price, this implementation required that the code share fare minus partner bid price fall into an open DAVN virtual bucket. This implementation is more consistent with DAVN treatment of own connecting itineraries. The prior BPS implementation obtained some of the benefits of DV, and was also more strict by using EMSRc values instead of minimum open bucket values as the own bid price. Because of these differences, this thesis's revenue gains for BPS in DAVN are not as high as those observed in Jain (2011).

The large revenue gains with DV in network A4 that were first presented in Jain (2011) with the exchange of dated bid prices from the prior time frame, were shown here to be similar with the exchange of current bid prices from time frame and daily optimization. The large magnitude of the revenue gains was due not only to the incorporation of partner bid prices into the code share valuations, but also because of the very high revenue value of code share itineraries in network A4, which caused an increase in average bid prices and generally stricter acceptance criteria for all traffic components. Thereby, the fare class mix of local, connecting, and code share itineraries was improved.

However, the promising results with DV in network A4 were shown to hold only partially in the different setting of alliance network E, as shown in Chapter 5. For alliance 1, which obtains a large share of revenues from code share and connecting traffic as compared with local traffic, and has relatively low average local and connecting fares relative to average code share fares, the gains from DV were higher than those for BPS in nearly all cases. At high demand, the benefits were larger if the competitor, alliance 2, used EMSRb as its RM method, but the revenue gains were still present, though slightly diminished, when alliance 2 also used network RM. At medium demand under DAVN, competitive feedback effects actually increased the revenue gains for alliance 1 from BPS or DV when the competitor also used DAVN.

On the other hand, alliance 2 was not found to benefit as much as alliance 1 from BPS or DV because of differences in its network characteristics. Alliance 2 obtains a larger share of revenues from local traffic as compared with the share from code share and connecting traffic, and has higher average local fares than alliance 1, as well as lower average code share fares. Also, applying network RM raised alliance 2's average connecting fares much more than for alliance 1, but did not raise average code share fares significantly. The combination of higher average local fares and lower code share fares caused spiral down for alliance 2 when it applied DV. When the competitor was also using network RM and DV, alliance 2 suffered revenue losses from using DV.

In the cases where the alliance partners use DAVN as their network RM method, either leg shadow prices from the network LP or EMSRc values for the flight legs may be used as bid prices. The results of this thesis showed that the revenue changes from BPS and DV are very similar regardless of which type of bid price is exchanged. The actual technique, whether it is BPS with single or dual control, or DV, is what ultimately determines the change in revenues. The changes in the component revenues and fare class mixes were also very similar for the two different types of bid prices. We can conclude that the exact form of the bid price is less important than whether it provides useful information to the partner about the value of a seat on the code share flight leg, and can thus be used by the partner to aid in making better code share availability decisions.

BPS with dual control was found to improve revenues in nearly all cases tested, providing revenue gains up to .40% above standard network RM. Gains were almost always positive, though sometimes only marginal. However, this was the only method that consistently performed well for each alliance in the various network, demand level, and RM method combinations. At higher demands in network E, this method produced much better results than at medium demands, indicating that as seats become scarce in that network, making better code share availability decisions is especially important for revenues.

On the other hand, BPS with single airline control can cause revenue declines from standard network RM by accepting too many code share bookings at the expense of potentially higher-revenue local or connecting bookings, as it overrides standard availability control. This result is true for both alliance networks. When both airlines use ProBP as their RM method and exchange bid prices simultaneously, the results of single and dual control are identical because the bid price sum equations of both airlines are the same. However, single and dual control produce different results in DAVN when using the bucketing criteria, because the airline partners may have different minimum open virtual buckets on their flight legs even if they exchange bid prices simultaneously.

DV is a method that should be approached carefully. It can produce large revenue gains in certain networks. However, it is necessary that code share itinerary fares be high-value relative to own local and connecting itineraries in order to justify incorporating the modified valuations into the RM optimization step, thus affecting the availability of own local and connecting itineraries. If code share fares do not provide high network value relative to own local and connecting itineraries, then it is not justified to modify their valuation in the optimizer because of the potentially detrimental effects this can have on availability decisions for the local and connecting components. In that case, using local valuation of code share itineraries instead, and applying BPS with dual control may be a more reliable, less risky solution for an alliance seeking to improve its code share availability control decisions.

6.2 Implications for Airlines

These results are generally encouraging and imply a trade off for airlines in terms of the costs of implementation. The exchange of leg bid price information first requires that code share itineraries are recorded and forecasted separately from local itineraries, which means that the airline must receive full information of the flight legs comprising the code share booking, and not only the legs that it operates. Next, the exchange of leg bid price information is required as a first step before any of the methods discussed and tested in this thesis can be used. It is then possible for the alliance to implement BPS with single airline control by comparing the code share fare with the sum of the bid prices on all the legs traversed. However, as we have seen in the results of this thesis, unless the partners use ProBP with simultaneous exchange of bid prices, BPS with single control will perform more poorly than BPS with dual control, and may result in revenue losses compared to standard network RM methods. Therefore, although it is simplest for airlines to implement BPS with single control as their code share RM method, it is not guaranteed that this method will provide revenue benefits if the airlines simultaneously use different bid prices for the same flight leg (the case with DAVN, asynchronous ProBP, and other methods). This is true even if optimization occurs frequently and very recent bid prices are exchanged.

There are technological complexities to dual airline control, which would require instant availability evaluation from both partners before a booking request is approved. Though code share seat allocation is not performed jointly over the entire alliance network, we have seen that BPS with dual control still represents an improvement. Gains can reach as much as +.43% in the best case scenario of ProBP at high demand, and +.40% for DAVN, can be marginal (+.02-.05%), or can even be slightly negative (-.02%) at low demand levels. The range of gains from BPS with dual control depends on the network structure, nature of demand, the optimization frequency, and the RM behavior of the competitor. Competitive feedback effects can reverse the benefits of some methods, especially if they are ill-suited to the airline's structure. This was demonstrated in the case of the losses experienced by alliance 2 when using DV simultaneously with alliance 1.

The cost and difficulty of implementing BPS with dual control is higher than BPS with single control, but the gains are certainly higher. Regarding DV, however, it is less clear that it would appeal to airlines because of the direct modification of inputs to the RM optimizer, and the effect that this modification would have on the availability decisions for own local and connecting itineraries. It may be more technologically difficult to dynamically modify the code share valuation, using the partner's bid prices, in the optimizer prior to the RM optimization step. The appeal of BPS with dual control is that it is a post-fact, add-on mechanism that does not require any modification to the operation of the existing RM system. Implementation is a one time investment, and the benefits will be compounded over time. Whether BPS is a worthwhile investment is ultimately for the airlines to decide.

For a large airline that participates in an alliance such as Lufthansa or United, with yearly revenues of over $30 billion, the actual gains from implementing dual control BPS, assuming an approximate percent revenue gain of +.15%, translate into over $45 million dollars per year. Considering the difficulties faced by large network airlines, which have struggled to report operating profits in general since airline deregulation and especially since the year 2000, small revenue benefits can make a big difference. This research has shown that alliance partners can cooperate and share their bid prices, whether they take the form of expected values of empty seats on flight legs, or network displacement costs approximated as shadow prices from a deterministic LP, to attempt to improve the total alliance revenues. Through the use of bid price sharing for post-fact code share itinerary availability control, or for dynamically valuing the code share itinerary's revenue contribution in the network optimizer, airlines in alliances can improve their revenues and affirm the benefits of entering into code sharing agreements.

6.3 Future Research Directions

The two networks, A4 and E, used in this research had specific network structures that resulted in somewhat different conclusions about the performance of BPS and DV. Expanding this research to networks of various other structures, and with other characteristics (i.e., the ratios of the average code share fare to local and connecting fares, and the proportions of revenue derived from the various traffic components) would help to compile a more holistic picture of the benefits of BPS and DV as a function of network structure.

Some literature on the alliance RM topic (Wright, 2010) has modeled the effects of partners choosing which bid prices to post for their own flight legs to maximize their own individual revenues, assuming that that the posted bid price is equal to the "transfer price", or the revenue that will be received by the operating partner if the itinerary is sold (revenues are not split according to a prorate agreement in this case). In addition to this "partner price" scenario, it is possible that some degree of bid price scaling (either up or down), in certain cases, would produce better availability decisions. A topic for further research is the effect on total alliance revenues of modifying bid prices for either mutual or individual benefit.

This thesis was concerned with the combined alliance revenues and has assumed that the revenue resolution contracts are fixed and have been negotiated such that each partner views his share as a fair division. Another direction for future research is to examine the effects of different revenue resolution schemes or prorate agreements between alliance partners on the behavior and incentives of individual participants.

Some airlines use fare adjustment (also called "marginal revenue optimization"), which decreases the fare inputs to the optimizer of lower class itineraries (Fiig et al., 2010). Some bid prices will be much lower if using fare adjustment. The performance of BPS may be significantly different if airlines are using this method. An idea suggested by Darot (2001) is that of bid price inference, where the lowest available fare on a flight leg is used as a pseudo-bid price. If actual bid prices are skewed downwards because of techniques like fare adjustment, then using lowest available fares may be a feasible alternative. Bid price inference is also applicable in the case when airlines do not have antitrust immunity to share bid prices, in which case communicating to each other the lowest available fares (which are public and would not require immunity) is still possible. Research on the success of BPS when using pseudo-bid prices because it is unsuitable or infeasible to exchange actual bid prices is another topic of interest.

We have seen that DAVN performs well as a network RM method because its composition of multiple heuristics makes it robust, and alone (without BPS) it produces large revenue gains even without frequent optimization. However, in the network E environment, applying BPS or DV to DAVN with time frame optimization resulted in large revenue losses. The work of Jain (2011) showed that a different, stricter implementation of BPS in DAVN, using the higher leg EMSRc values rather than minimum open buckets as own bid prices resulted in better performance. Also, using the total code share fare minus the partner bid price for the calculation of virtual bucket booking limits also produced stricter EMSRb virtual bucket booking limits and better revenues. Because DAVN comprises multiple heuristics, it may require airline-specific tweaking to obtain maximum performance. Further research into the adjustments needed to improve the performance of BPS in DAVN, and in what situations such adjustments are appropriate, would be of practical importance.

Also of practical importance to the industry is to test BPS and DV with different RM combinations that are not limited to the O-D control methods of DAVN and ProBP. We have tested various network and leg RM combinations in network A4, but it is important to continue this research for networks of varying structures as well, and confirm whether BPS with dual airline control remains the only method that consistently delivers revenue gains, though marginal in some cases.

To the author's knowledge, most of the airlines in alliances are only just taking the first steps towards sharing bid price information and incorporating it into their code share availability decisions. A major limitation of the models and methods proposed in the literature thus far is that they were tested on relatively small and simple hypothetical networks. Other than this thesis, the author is unaware of literature that also examined the performance of alliance RM in a competitive alliance environment. Once such alliance RM systems are in place as those proposed here and in the literature, data documenting the code share availability decisions and actual mechanisms used by airlines in real world competitive and network scenarios can be collected. The success of the various methods proposed here and elsewhere in the literature can then be validated according to real airline data.

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